08

7.9 - 1 0.0.0 1.

(E79-10001) A COMPREHENSIVE DATA PROCESSING PLAN FOR CROP CALENDAR MSS SIGNATURE DEVELOPMENT FROM SATELLITE IMAGERY: CROP IDENTIFICATION USING VEGETATION PHENOLOGY Final (Kansas Univ. Center for Research,

CR-157891

N79-13424

Unclas

G3/43 00001

2312B

THE UNIVERSITY OF KANSAS CENTER FOR RESEARCH, INC.
2291 Irving Hill Drive—Campus West
Lawrence, Kansas 66045

THE UNIVERSITY OF KANSAS CENTER FOR RESEARCH, INC.

~~2291 Irving Hill Drive — Campus West~~
Lawrence, Kansas 66045

Telephone:

A COMPREHENSIVE DATA PROCESSING PLAN FOR CROP CALENDAR MSS SIGNATURE DEVELOPMENT FROM SATELLITE IMAGERY - CROP IDENTIFICATION USING VEGETATION PHENOLOGY

C.A. Hlavka
S.M. Carlyle
R.M. Haralick
R. Yokoyama

The University of Kansas Center for Research, Inc.
Remote Sensing Laboratory
RSL Technical Report 286-5
Final Report

July 1978

Supported by:

NASA GODDARD SPACE FLIGHT CENTER
Greenbelt, Maryland 20771

Contract NAS5-20943

(on back)

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
286-5		
4. Title and Subtitle A COMPREHENSIVE DATA PROCESSING PLAN FOR CROP CALENDAR MSS SIGNATURE DEVELOPMENT FROM SATELLITE IMAGERY: CROP IDENTIFICATION		5. Report Date July 1978 6. Performing Organization Code
7. Author(s) R.M. Haralick, C.A. Hlavka, S.M. Carlyle, R. Yokoyama		8. Performing Organization Report No.
9. Performing Organization Name and Address		10. Work Unit No. 11. Contract or Grant No. NAS5-20943
12. Sponsoring Agency Name and Address James C. Broderick - Technical Monitor NASA Goddard Space Flight Center Greenbelt, MD 20771		13. Type of Report and Period Covered Type III, Final Report 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

The use of multi-temporal, multi-spectral LANDSAT data for mapping locations of several types of crops, especially winter wheat, is compared using some traditional classification procedures and an innovative method which attempts to take account of the phenological growth states of crops. The use of data from two or three observations lead to improved vegetation mapping over use of a single observation date.

The phenological growth procedure models spectral reflectance explicitly as a function of crop maturity rather than a function of observation date. This means that instead of stacking spectral vectors of one observation on another, as is usually done for multi-temporal data, we try to establish a correspondence of time to growth state which minimizes the smallest difference between the given multi-spectral, multi-temporal vector and a category mean vector. The phenological growth procedure discriminated crop type about as well as the more conventional methods and provided some

(continued on back of page)

17. Key Words (Selected by Author(s))	18. Distribution Statement
LANDSAT, agricultural remote sensing, phenology, crop signature, multi-temporal data	

19. Security Classif. (of this report)	20. Security Classif. (of this page)	21. No. of Pages	22. Price*
Unclassified	Unclassified	118	

*For sale by the Clearinghouse for Federal Scientific and Technical Information, Springfield, Virginia 22151.

4. USING VEGETATION PHENOLOGY

16. additional crop maturity information at each observation time.

This report also includes a literature survey of vegetation classification using multi-temporal LANDSAT imagery.

TABLE OF CONTENTS

TABLE OF CONTENTS (continued)

LIST OF FIGURES

LIST OF FIGURES (continued)

LIST OF TABLES

0.0 SUMMARY

An important application of LANDSAT data is the estimation of crop acreage and agricultural land use mapping. We have investigated the use of multi-temporal, multi-spectral data in small area agricultural vegetation mapping in five Kansas LACIE Intensive Test Sites and a portion of Madison County, Iowa.

The methods of classification we have used include the following:

(1) Linear discrimination, a method which assumes that the signals from each crop have a Gaussian distribution with equal covariance matrices.

(2) A Bayes table look-up method, which we have developed in previous vegetation mapping investigations.

(3) Unsupervised clustering.

(4) An innovative method which attempts to take account of the phenological properties of growing crops.

In this final report, we concentrate on reporting on the phenological method of crop identification. The method involves the creation of crop signatures which characterize multi-spectral observations as phenological growth states. The phenological signature models spectral reflectance explicitly as a function of crop maturity rather than a function of date. This means that instead of stacking spectral vectors of one observation on another, as is usually done for multi-temporal data, we try to establish a correspondence of time to growth state which minimizes the smallest difference between the given multi-spectral multi-temporal vector and a category mean vector. The results of applying it to the identification of winter wheat and of corn show (1) the method is capable of discriminating crop type with about the same degree of accuracy as more traditional classifiers; (2) the use of LANDSAT observations on two or more dates yields better results than the use of a single observation; and (3) it shows some potential to label degree of maturity of the crop, as well as crop type.

In the phenological discrimination process, each multi-spectral observation from a pixel at a single observation time is labeled as part of a cluster within crop type. The clustering method was designed so that each cluster would contain observations at the same degree of maturity. Our experimental results are consistent with the interpretations of the clusters, but not conclusive. There is significant correlation between factors such as irrigation and growth rate. In order to find out what factors the clusters are associated with and in order to refine the clustering process, further tests are needed using ground truth with detailed information on crop condition.

1.0 LITERATURE REVIEW: THE USE OF LANDSAT MULTI-TEMPORAL DATA IN AUTOMATIC VEGETATION MAPPING

The use of LANDSAT multi-temporal data for classification of vegetation is a recent technique made possible by development of techniques of accurate registration of data from two or more observations of the same area. Computer compatable tapes (CCT's) of registered scenes of geographical areas observed at different dates within a growing season are available to researchers from NASA in Houston and through the LACIE (Large Area Crop Inventory Experiment) program.

Through the use of multi-temporal data, it may be possible to produce very accurate vegetation maps and crop acreage estimates. The use of multi-temporal data increases the number of channels of information available for the classifier to up to four times the number of observations, as there are four spectral bands of data collected by LANDSAT: MSS Band 4 - (.5-.6 μm), MSS Band 5 - (.6-.7 μm), MSS Band 6 - (.7-.8 μm), MSS Band 7 - (.8-1.1 μm). The reasons this increase in information could increase classification accuracy are:

(1) Different sets of classes may be separable at different times of the year.

(2) The measurements between classes may be more easily separable in a higher dimensional measure space. Figure 1 illustrates this effect for data in one spectral band on two observation dates. The measurements for the two classes to be distinguished are well separated in the plane, but overlap for individual dates.

(3) Understanding of vegetation phenology could be applied to the temporal information supplied, perhaps in conjunction with crop calendar information.

Classification of water, shrubs, and trees in the Great Dismal Swamp using a winter LANDSAT scene and a spring LANDSAT scene corresponded well with a map made from aerial infra-red photographs (Gammon and Carter, 1976). In

the winter, the types of evergreens and standing water were easy to distinguish. In the spring, it was possible to separate the classes of deciduous greenery.

Other investigators have experimented with classification of crop and forest land (Von Steen and Wigton, 1976; Megier, 1977) and have reported increases in classification using multi-temporal LANDSAT data. Von Steen and Wigton reported an increase in overall classification accuracy of Missouri cotton, corn, soybeans, and grass discrimination to 58.8% over the best single date classification accuracy of 50.8% using three observation dates late in the growing season.

Some investigators have noted that the benefits of multi-temporal LANDSAT data are dependent upon data acquisition dates (Landgrebe, 1974; Kalensky and Scherk, 1975). Landgrebe reported a decrease in classification accuracy of Illinois corn and soybeans using the best date/band combinations from three observations: August 9, September 12, and October 2. However, classification using MSS bands from September 12 and October 2 late season and therefore non-optimal observation dates, was better than classification using data from either of these dates alone. Similarly, Kalensky and Scherk noted that classification accuracy of forest maps was not improved significantly by multi-temporal classification, but was consistently close to the best observation date classification. It seems then that higher dimensionality of multi-temporal information can be used to achieve good classification of vegetation when optimal observation dates are not available, such as when an agricultural scene is obscured by cloud cover on mid-season dates of LANDSAT overpasses.

Most investigators have used maximum likelihood supervised discrimination with the assumption that the measurement vectors from each class of data have a Gaussian distribution. The simplest classification with this method assumes

that the covariance for each vegetation class is the same. It turns out that in this case the maximum likelihood rule assigns measurements to the class whose mean measurement is nearest. If the a priori probability of each class is assumed to be the same, the measure of "nearness" is the Mahalanobis distance:

$$(x - u_i)' \Sigma^{-1} (x - u_i)$$

where

x = measurement to be classified

u_i = mean measure of the i-th characters

Σ = the covariance matrix

Multi-temporal data has been used in the application of non-parametric classification techniques as well. LeToan (LeToan et. al., 1977) have tested methods of supervised, non-parametric discrimination to estimate acreages of rice fields. The best acreage estimate of rice with multi-temporal data used barycentric distance. The barycentric distance between two measurements $x_1 = (x_{11},\ldots,x_{1N})$ and $x_2 = (x_{21},\ldots,x_{2N})$ is a weighted Euclidean distance:

$$d^2(x_1,x_2) = \sum_{j=1}^{N} k_j(x_{1j} - x_{2j})^2$$

where the weights k_j are chosen to optimize the classification of a sample within the agricultural scene. Kauth (Kauth, et. al., 1977) has developed BLOB, an unsupervised clustering technique that incorporates both spatial coordinates and multi-temporal multi-spectral LANDSAT gray tones into measurement vectors.

2.0 THE DATA

There were five LACIE Intensive Test Sites, all in Kansas, involved in the study. We received a tape for each study site which contained registered ERTS images for that site for a number of dates in the 1973-1974 crop year, together with an aerial photograph and overlaying transparency showing ground truth and some soil maps from the Johnson Space Center. Two of these sites, Morton County and Rice County, were analyzed extensively.

The General Electric Space Division in Beltsville, Maryland, provided us with a tape containing resampled (50 meter x 50 meter) LANDSAT data of Madison County, Iowa for four dates in the 1975 growing season and a county map with corn and soybean fields drawn in it.

Weather data for all the areas studied was obtained from Climatological Data, Iowa 1975-1976 and Climatological Data, Kansas 1973-1974, published by the U.S. Environmental Service. Additional information on weekly precipitation in Morton County and the condition of wheat in southwestern Kansas was extracted from the 1973-1974 issues of Kansas Weekly Weather-Crop Reports, obtained from the Kansas Crop and Livestock Reporting Service.

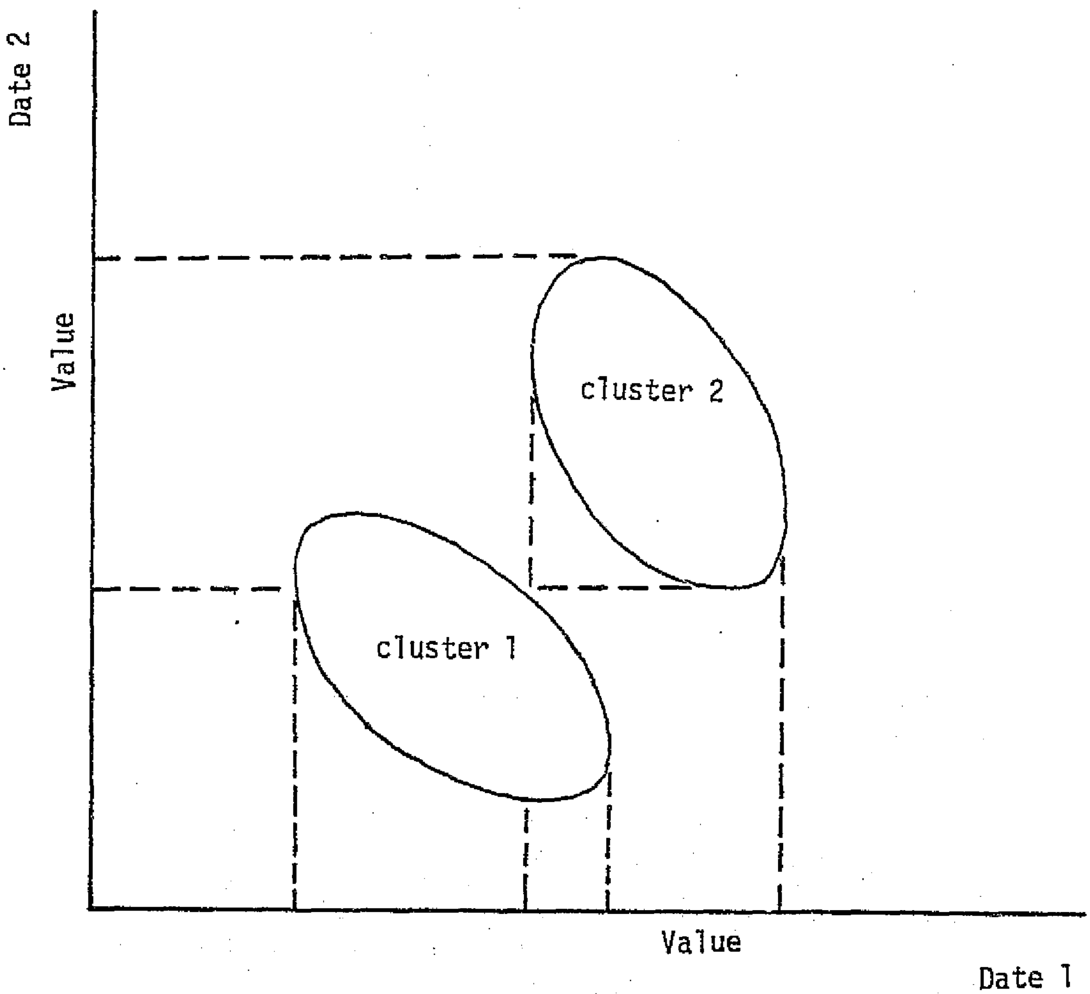


Figure 1. Two Clusters of Two Date Observations

An additional band of crop type ground truth was created for the areas which have been studied intensively, Morton and Rice Counties. These are "shrunken" ground truth maps in which pixels on boundaries are removed from ground truth. These bands of ground truth were created after it was determined using linear discrimination (see Section 4.1), that there was some small amount of temporal and ground truth misregistration. In further data analysis, the "shrunken" ground truth was used in the selection of training data and in evaluation of our classified images.

The 128 gray tone levels of the LANDSAT data were quantized, using an equal interval algorithm, to 32 levels. For each band, the quantizer finds the minimum and maximum LANDSAT gray tone level, MIN and MAX, and converts the gray tone level G to $\frac{G - MIN}{MAX - MIN + 1} * 32$. This operation is done for three reasons:

(1) Reduction of storage space of the SIF image on disk and image processing time.

(2) Rendering the data suitable for classification with some of the computer routines we used. The table look-up procedures, Bayes, and second order phenological discrimination, require quantized data because the PDP-15 does not have sufficient core for storing tables for 128 level data.

(3) The quantization roughly corrects for camera angle, sun angle, and atmospheric effects for different observations. The brightest and darkest pixels for any observation MSS band combination are always Ø and 31 on the quantized SIF image. These pixels are objects like roads, bare ground, and water which should look the same from one time to the next. All gray tone levels are normalized with respect to these objects.

3.1 Preprocessing of the Madison County, Iowa Data

Ground truth for the Madison County, Iowa image was quite sparse and some fields shown on the map were impossible to locate, due to their small size. Two areas of interest containing concentrations of ground truth fields identified on the county map were isolated with the aid of the

3.0 PREPROCESSING OF THE KANSAS DATA

Copies of registered temporal ERTS (LANDSAT) computer compatible tapes for five test sites were provided by the Johnson Space Center.

KANDIDATS (KANsas Digital Image DATa System) is an image processing software package developed at the University of Kansas Center for Research, Inc., (CRINC). It is designed for the PDP-15 computer and the IDECS, a hybrid image processing and television display system developed at CRINC. The digital images on the tapes were converted to a Standard Image Format (SIF) by use of KANDIDATS image processing routines. This is done so that all images can be accessed and manipulated using standard system routines. SIF allows multi-digital images containing both "picture" and "map" information, as well as the image's processing history. Figure 2 illustrates the file structure.

Since each image covered more than the study site of interest, it was desirable to "trim" off excess to save storage space and later image processing time. Black and white transparencies of the whole ERTS frame were compared to maps of the area to locate each study site. After outlining a study site on the transparency with a grease marker, sections of the whole frame were displayed on the IDECS image display system in order to locate the area of interest. By this method the section containing the study site was found and a subimage was produced for further processing.

Two bands of ground truth (crop type and soil type) were then processed to overlay the multi-picture subimage of the study site. This was done by trial and error, visually on the IDECS television display, using the KANDIDATS software package to compute rotations and distortions. Appendices B, C, and D contain details of rotations and distortions for Rice, Morton, and Saline counties, respectively.

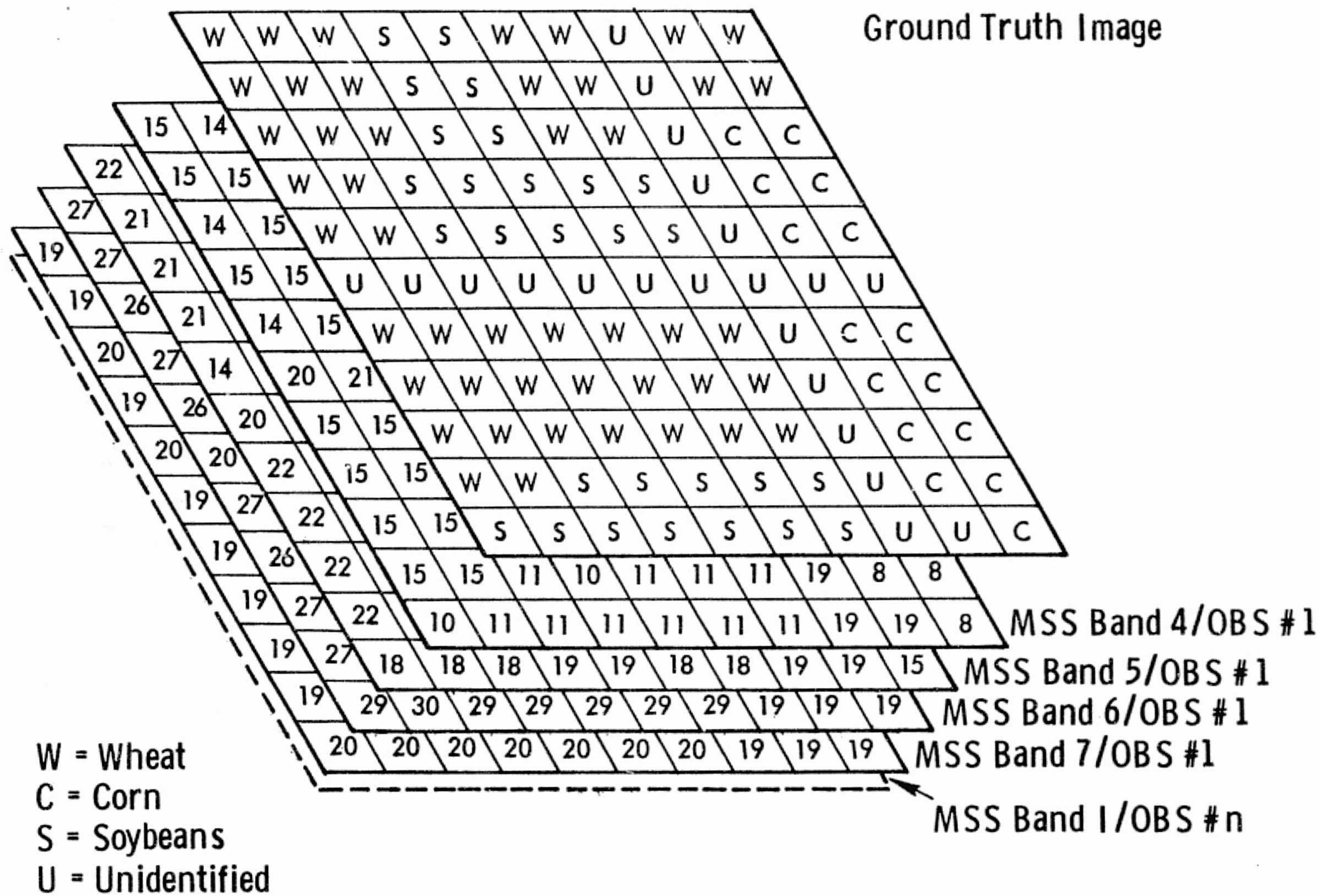


Figure 2. Illustration of KANDIDATS Standard Image File (SIF) for storing scene graytones and corresponding ground truth.

IDECS and two subimages created. The total ground truth used consisted of polygonal areas within 13 corn fields, 3 soybean fields, and the small town of Winterset. The LANDSAT gray tones were quantized down to 32 levels, in the same way as with the Kansas data.

Further investigation, through the use of graphs of the means and of ranges of the reflectivity of the various soil types, crop types and dates for Rice County showed noticeable differences in the means within a date for the different soil types. However, the relation between the means is clearly different from one date to the next. Thus, the underlying soil type not only introduces variation in reflectivity as a result of its own reflective properties when crop cover is less than complete, but also introduces significant variation indirectly due to its attributes which contribute to the growth rate of a particular crop. It is easy to imagine the complicated interaction between soil, weather, topology, and crop type.

In an attempt to counter atmospheric affects, straight band ratioing was tried. This gave 46.4% total correct classification; again a non-significant increase.

Errors of the third type were easily verified from the coordinates of those pixels incorrectly classified. No investigation was carried out to check the correctness of the ground truth.

In analyses of Morton County, the BMDP7M program gave 74.1% total correct classification, with 84.1% for wheat, 70.2% for the grass category, 59.4% for corn, 71.8% for summer fallow, 40.0% for non-agricultural, 43.2% for grain sorghum, and 72.7% for rye.

Note that the percentage of correct classification dramatically increased for most crop types. This improvement might be attributed to two things:

(1) The excessive rainfall received by Rice County which resulted in some local flooding.

(2) The Morton County scene observation dates better cover the growth cycles of the crops of interest.

4.0 ANALYSIS OF KANSAS LACIE INTENSIVE TEST SITES

Some traditional methods of vegetation classification were used on the five Kansas LACIE Intensive Test Sites. These included linear discrimination, Bayes table look-up classification, and unsupervised clustering.

4.1 Linear Discrimination

Our image analysis began with the use of linear discriminant algorithms on unquantized LANDSAT data on the Honeywell 6660 at the University of Kansas Computation Center. The data samples were input on cards. The details of this analysis were reported in our Second Progress Report.

The programs used were BMDPD, a general data describing program, and BMDP7M, a discriminant analysis program (Dixon, 1975). Initially, an intensive analysis was carried out on the Rice County site. The total correct classification was 46.2%, with 39.7% of the wheat correctly identified, 37.5% of the grass category, 75.6% of the corn, 28.8% of the summer fallow, 14.3% of the non-agricultural, and 43.2% of the grain sorghum.

At this point, four possibilities were suggested for the poor rates of success:

(1) Different soil types were significantly contributing to the variation in the reflectivities.

(2) Atmospheric effects were contributing significant variation to reflectivities.

(3) Misclassified pixels were on the edges and attributable to temporal and ground truth misregistration.

(4) The ground truth for some fields were incorrect or had changed over the period of observation.

To correct for the first source of possible error, each reflectance band was regressed on to soil type, using the REGRESS program (Neely, 1971-1974). The equations of all significant regressions were used to calculate residuals for the BMDP7M program. However, this led to only a 47.1% total correct classification, a non-significant increase.

MSS Band4/October 1973 - MSS Band4/April 1974, and MSS Band4/June 1974 - MSS Band4/July 1974 with Bayes decision rule parameters $\alpha = .40$ and $\beta = 0.028$.

Spatial post-processing was also tried on the Rice County image. This is a reassignment of the categories based on geometric considerations. The first spatial operation on a category map was to change to reserve decision category assignments of resolution cells whose neighbors differed. If a resolution cell has more than n neighboring resolution cells whose assignment is different, then its category assignment becomes reserved. This has the effect of eliminating small regions from the classified image. The shrunken map is then iteratively filled back assigning resolution cells of reserved decision to the categories of its nearest assigned neighbor. The effect of the post-processing was to increase overall correct classification. The most improvement was noted with a shrink with a maximum of one dissimilar neighbor of the 4 adjacent neighbors followed by one fill. For example, the overall correct classification described above with three band pairs was improved to 77%, with 95% correct identification of wheat, 57% for grain sorghum, 88% for corn, and 20% for summer fallow.

The Saline County image was processed using fewer different parameters. The error rate step selected the following band pairs as best for the discrimination step:

MSS Band 4/October 1973 - MSS Band 6/October 1973

MSS Band 4/October 1973 - MSS Band 4/April 1974

MSS Band 4/July 1974 - MSS Band 6/July 1974

for the discrimination of the following categories: wheat, grass, corn, soybeans, non-agricultural, and grain sorghum. The results of this data set were typically worse than those of Rice County. Poor date-to-date registration of this data set is suggested as a partial cause.

4.2 Pattern Discrimination with a Bayes Table Look-Up Rule

Four test sites were processed using the table look-up rule, using the KANDIDATS/BAYES package routines. (For a discussion of the table look-up method, see Haralick, 1976). These were Rice, Saline, Morton, and Finney Counties. Sites were typically processed in the following manner after preprocessing in the manner described in Section 3.0:

(1) An error rate measure (the sum of the Bhatacharyya coefficients over all pairs of crop categories) was run for all band pairs for each site. This gave a measure of which band pairs would produce the best results for discrimination. The best band pairs for each site are given in succeeding sections.

(2) The three best band pairs were used in the table look-up processing. Several levels of error parameters were applied to each image. The results are reported in the following sections.

(3) The best bands were rotated onto the principle axis by a principal component analysis. The resultant image was then used as input to steps (1) and (2) above.

The image for Rice county was intensely studied. Several band pair sets were tried along with several different decision rules. The following band pairs were used with a majority vote decision rule:

MSS Band 5/July 1974 - MSS Band 7/July 1974

MSS Band 4/October 1973 - MSS Band 6/October 1973

MSS Band 4/April 1974 - MSS Band 6/April 1974

This resulted in approximately 50% overall correct identification with 6 or 8 crop categories. Classification of 4 or 8 categories using the intersection table look-up rule with two or three band pairs was also experimented with, yielding similar results. Table 4.2.1 shows the results of this method of classification using the band pairs MSS Band4/July 1974 - MSS Band 7/July 1974,

CONTINGENCY TABLE FOR RICEBOOMB - 19 RICEBGB13 - 1 SCALE FACTOR 10** 0

β = .028
α = .4
COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GSORG	CORN	SUFAL	TOTAL	#ERR	% ERR	% SD
UNKWN	3056	2188	795	348	110	6497	0	0	0
WHEAT	211	441	32	19	12	715	63	13	1
GSORG	192	106	211	7	3	519	116	35	1
CORN	136	2	11	259	0	408	13	5	0
SUFAL	60	41	20	0	22	143	61	73	4
TOTAL	3655	2778	1069	633	147	8282	253	31	0
#ERR	0	149	63	26	15	253	****	****	****
% ERR	0	25	23	9	41	24	****	****	****

Table 4.2.1 Contingency table for Rice County image with no spatial processing

62% of the wheat identified
14% of the non-wheat identified as wheat

Bayes discrimination of the Morton County image followed the steps outlined above. The error rate measure selected the following bands as best for discrimination:

MSS Band 5/May 9, 1974 - MSS Band 7/May 9, 1974

MSS Band 5/May 27, 1974 - MSS Band 7/May 27, 1974

MSS Band 5/June 2, 1974 - MSS Band 7/July 2, 1974

Discrimination with the Bayes intersection table look-up methods gave 45% overall correct classification, with 49% of the wheat correctly identified, 48% for grass, 24% for corn, and 49% for summer fallow. It is interesting to note that with linear discrimination better results were obtained from the Morton County site than the Rice County site; however, with the Bayes technique, just the opposite was found.

Further processing of the Morton County image included rotating the best bands on their principle axis for a principle component analysis. This did not result in significantly improved identification.

The last site processed was Finney County. Again, the steps outlined above were followed for this site. The error rate measure selected the following band pairs.

MSS Band 5/October 1973 - MSS Band 7/October 1973

MSS Band 5/April 1974 - MSS Band 7/April 1974

MSS Band 5/July 1974 - MSS Band 7/July 1974

The results were 32% overall correct classification with 41% correct classification of wheat, 16% for grass, 44% for corn, 5% for summer fallow, and 10% for grain sorghum. Again, principal component analysis was performed with no significant improvement in classification accuracy.

CONTINGENCY TABLE FOR MORISBOOMB - 23 MORISBOBYO - 1 SCALE FACTOR 10** 0

β = .0245
α = .35
COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GRASS	CORN	SUFAL	GSORG	RYE	TOTAL	#ERR	% ERR	% SD
UNKWN	8593	2085	505	141	1392	72	17	12805	0	4	0
WHEAT	1931	1962	1	0	89	0	2	3985	92	4	0
GRASS	529	7	490	0	2	0	0	1028	9	2	0
CORN	541	4	0	175	6	14	0	740	24	12	0
SUFAL	1583	9	3	5	1521	2	4	3127	23	1	0
GSORG	194	1	0	2	10	13	0	220	13	50	1
RYE	161	27	0	0	47	0	16	251	74	82	2
TOTAL	13532	4095	999	323	3067	101	39	22156	235	25	0
#ERR	0	48	4	7	154	16	6	235	****	****	****
% ERR	0	2	1	4	9	55	27	16	****	****	****

Table 4.2.3 Contingency table of the Morton County image

CONTINGENCY TABLE FOR RICEBOOMB - 19 RICEBG113 - 1 SCALE FACTOR 10** 0

β = .028
α = .4
COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GSORG	CORN	SUFAL	TOTAL	#ERR	% ERR	% SD
UNKWN	0	4581	1092	776	48	6497	0	0	0
WHEAT	0	681	21	13	0	715	34	5	0
GSORG	0	188	298	33	0	519	221	43	2
CORN	0	39	8	360	1	408	48	12	1
SUFAL	0	82	31	1	29	143	114	80	3
TOTAL	0	5571	1450	1183	78	8282	417	35	0
#ERR	0	309	60	47	1	417	****	****	****
% ERR	0	31	17	12	3	15	****	****	****

Table 4.2.2 Contingency table for Rice County image with spatial processing

Doubling every pixel vertically and horizontally before clustering improved results considerably. This increased the image size by a factor of four because such pixel has replaced by four copies of itself. The spatial clustering not only picked up more fields, but the shapes of the fields were better.

4.3.1 Unsupervised Clustering of the Morton County Image

The Morton County image was expanded in the manner described in the previous section. MSS Bands 5 and 7 of the October 23 and July 2 dates were used in the spatial clustering step. This resulted in the definition of 607 regions on the image. MSS Bands 5 and 7 on all five observation dates were used for spectral clustering. The 607 regions were reduced to 131 classes in 7 iterations and into 23 classes in 10 iterations. Visual examination of print-outs of the images showed that a group of pixels was labeled in the interior of almost every ground truth field. Also, pixels within each field were labeled the same, because of the spatial clustering.

Table 4.3.1 shows a contingency table comparing ground truth versus the 23 class clustered image. In order to create the contingency table, the expanded image had to be shrunk back down to the original unclustered image size. This caused the disappearance of many of the 23 classes, which were small and not associated with major types of land use, which is why the table shows no pixels for some cluster members. Note that most clusters include pixels from more than one ground truth class. This shows that fields of different crop types are often more spectrally alike than fields of the same crop. Table 4.3.2 shows the contingency table of ground truth versus the 131 clusters. One would expect that with such a large number of clusters, each cluster would represent a sub-class of a single crop type. However,

4.3 Unsupervised Clustering

Some unsupervised clustering was performed on the LACIE Intensive Test Sites in Rice, Morton, Saline, and Finney Counties in Kansas. As the term implies, unsupervised clustering is a classification process that does not use a training data set. The clustering is done in two steps. In the first step, spatial clustering is performed to determine spectrally homogeneous areas in the image by gradient thresholding. This process creates an image in which boundary pixels are labeled "Ø" and contiguous groups of pixels within boundaries are uniquely labeled. In the second step, contiguous areas are clustered so that pixels in spatial clusters which are spectrally similar have the same label. This is an iterative process. The spectral similarity is measured by the Euclidean distance function in the multi-dimensional space defined by the quantized ERTS bands on the original image. In addition to the steps just described, some noise cleaning and constrast enhancement were performed on the images to improve the clustering.

The gradient function used for spatial clustering is the Robert's gradient defined to operate on multi-band images, as each test site image is. It was found that using pre and post wheat harvest dates (October and July) gives a much better definition of the field boundaries than a single date. Also MSS Bands 5 and 7 have better spatial definition than Bands 4 or 6. Using all bands on all dates would give poor boundary definition because of inexact registration of bands. It was found by use of the IDECS television display that average registration was off sometimes by one or two cells between dates.

TABLE 4.3.1

CONTINGENCY TABLE OF 23 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Unknown	1434	761	1105	102	32	0	18	0	59	48	0	14	1	0	0	0	13	0	8	0	0	0	0
Wheat	1542	124	106	0	13	0	3	0	0	0	0	98	0	0	0	0	0	0	0	0	0	0	0
Grass	0	0	622	0	0	0	0	0	0	79	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn	1	36	184	9	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0
S. fallow	155	327	1022	371	0	0	0	0	0	0	0	0	0	0	0	0	37	0	0	0	3	0	0
G. sorghum	15	19	12	11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rye	8	14	0	65	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	3154	1281	3051	558	45	0	23	0	59	127	0	112	0	0	0	0	0	0	8	0	0	0	0

there are several clusters containing substantial numbers of pixels from two ground truth crop types. Most notably, several clusters are divided between wheat and summer fallow. There are two possible reasons for this. One reason is that the ground truth is in error. Another explanation is that unusual conditions are causing some wheat and some fallow fields to look very similar. Perhaps volunteer wheat grew in some of the summer fallow fields. The 1973-1974 growing season in Morton County was very dry, with the result that some of the wheat fields were abandoned (see Appendix H).

TABLE 4.3.2 (continued)

CONTINGENCY TABLE OF 130 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47
Unknown	2	0	1	0	63	2	0	28	0	178	475	0	36	26	0	0	0	6	10	0	2	5	1	3
Wheat	3	0	78	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0
Grass	0	0	0	0	0	0	0	0	0	0	622	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn	0	0	0	0	16	9	0	15	0	0	6	0	0	0	0	0	0	0	19	0	0	0	0	0
S. fallow	0	0	0	0	0	0	0	0	0	90	232	0	0	225	0	0	0	10	4	0	0	0	0	0
G. sorghum	0	0	0	0	0	0	0	10	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rye	0	0	0	0	0	0	0	0	0	13	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Total	5	0	79	0	79	11	0	53	0	286	1335	0	37	251	0	0	0	16	33	0	3	5	2	3

TABLE 4.3.2 (continued)

CONTINGENCY TABLE OF 130 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	48	49	50	51	52	53	54	55	56	57	58	59	60	61	62	63	64	65	66	67	68	69	70	71
Unknown	3	18	0	32	0	146	13	6	0	4	7	0	0	3	0	0	1	0	6	0	0	10	0	0
Wheat	13	41	0	65	0	6	0	0	0	0	0	0	5	0	0	0	0	0	90	0	0	0	0	0
Grass	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	0	0	0
S. fallow	0	0	0	0	0	20	0	0	0	0	0	0	0	117	0	0	0	0	0	0	0	0	0	0
G. sorghum	0	0	0	0	0	0	0	15	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0
Rye	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	16	59	0	105	0	166	13	21	0	4	33	0	5	120	0	0	9	0	96	0	0	13	0	0

TABLE 4.3.2 (continued)

CONTINGENCY TABLE OF 130 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	72	73	74	75	76	77	78	79	80	81	82	83	84	85	86	87	88	89	90	91	92	93	94	95
Unknown	4	1	0	2	0	1	0	4	0	0	5	0	0	0	3	7	54	0	0	3	26	0	2	3
Wheat	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	2	0	0	0
Grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn	0	56	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	2	0	0	15	0
S. fallow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0
G. sorghum	0	0	0	0	0	0	0	1	0	0	4	0	0	0	0	8	0	0	0	0	0	0	0	0
Rye	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	4	57	0	2	0	1	0	5	0	2	9	0	0	0	7	19	54	0	0	5	28	0	17	8

TABLE 4.3.2 (continued)

CONTINGENCY TABLE OF 130 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	96	97	98	99	100	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115
Unknown	6	0	0	0	4	10	7	0	0	0	0	0	0	0	0	0	0	4	0	0
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	6
Grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Corn	2	0	0	0	0	0	18	0	0	0	0	3	0	0	0	0	0	0	0	0
S. fallow	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0
G. sorghum	0	0	0	0	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Rye	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Total	8	0	0	0	10	43	25	0	0	0	0	3	0	0	0	0	0	7	0	6

TABLE 4.3.2 (continued)

CONTINGENCY TABLE OF 130 CLUSTERS VERSUS GROUND TRUTH - MORTON COUNTY

COL = CLUSTER NUMBER
ROW = TRUE CATEGORY

	116	117	118	119	120	121	122	123	124	125	126	127	128	139	130	
Unknown	1	0	0	0	0	0	4	0	8	0	0	1	3	0	6	
Wheat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Grass	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Corn	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
S. fallow	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
G. sorghum	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	
Rye	0	0	0	0	0	0	0	2	0	0	0	0	0	2	0	
Total	1	0	0	0	0	0	4	2	8	0	0	1	3	2	0	

5.0 PHENOLOGICAL DISCRIMINATION MOTIVATIONS

A fundamental problem in crop identification with LANDSAT data is the number of variables in addition to crop type that influence observed spectral reflectance values from a crop canopy. Among these is degree of maturity of the crop, or phenological stage, which can vary even within a small area at a given time. For example, Nalepka (Nalepka, 1977) has observed significant differences in phenological stage of winter wheat between fields in Kansas LACIE Intensive Test Site and even between areas within the same field. Furthermore, it is possible for one field to be at the same stage of maturity as a neighboring field was 18 days earlier. Differences in growth stage are particularly significant in the later parts of the growing season of winter wheat due to the rapid changes in appearance that occur with maturation, cutting, and in some cases, tilling of the fields.

We have experimented with a crop discrimination method that takes account of and utilizes this growth stage factor. Multi-temporal classification is usually carried out by simply appending the spectral reflectance vectors observed at one time with the spectral reflectance vectors observed at another time. Then one processes the new data set as if it were vectors like a single observation data set. The usual crop signature is a set of these multi-temporal and multi-spectral vectors associated with the crop type. We use a crop signature which consists of sets of multi-spectral vectors associated crop type-growth states. Associated with each crop is an "M-th order signature" which is a set of M +1-tuples $(g; \alpha_1,\ldots,\alpha_M)$ where g is a growth state for the crop and $(\alpha_1,\ldots,\alpha_M)$ is an ordered set of gray tone values for a subset of size M of the four LANDSAT MSS bands. We say that a pixel is of a crop if: (1) Each set of observed gray tones on

a particular date is consistent with some growth stage g described in the signature and (2) These g's are consistent with what we know about vegetation phenology: the g's must be chronologically ordered. Classification is done by eliminating inconsistent category choices. If more than one category is left after the process of elimination, then the pixel is unclassified.

To illustrate the meaning of this, consider a 2-band simple first-order example. Suppose observations (α_1, α_2) and (α_1', α_2') of a small patch of ground are taken at times t_1 and t_2 using the bands b_1, b_2. This can be classified by determining, for each category c, the first growth stage g_1 such that (g_1, α_1) and (g_1, α_2) is in the signature for c. If there is no such growth state, then the category c is not consistent with the observed spectral reflectance and c is not a possible classification for the pixel. If there is not a later growth stage $g_2 > g_1$ of category c such that (g_2, α_1') and (g_2, α_2') is in the signature for c, then c is not a possible classification for the pixel. We may also impose restrictions on the growth states because only certain growth states may be possible at a particular observation time. In that case, c will not be a possible choice if the only growth states consistent with the observed spectral reflectances are not possible for the observation times.

The implementation of this discrimination method is in two steps: (1) Signature creation using a training set. We experimented with using field average gray tones and resampled gray tones of randomly chosen individual pixels within ground fields as training sets, and (2) Classification of the picture using the signature. We have tested the method using first and second-order signatures. The details of implementation in these two cases is described in following sections.

5.1 First-Order Phenological Discrimination

First-order category signatures can be estimated from training sets with an iterative procedure consisting of a step of dynamic programming minimization followed by averaging very much in the spirit of the ISODATA clustering technique (Ball and Hall, 1965). Let $x(i,j,t)$ be the observed spectral reflectance in the i-th band, j-th sample (pixel or average over a field) of a crop type, taken at the t-th observation time. The set $\{x(i,j,t) \mid i = 1,\ldots,I;\ j = 1,\ldots,J;\ t = 1,\ldots,T\}$ is the training set for the category. Let u be the current mean spectral signature for the category of interest. $u(g,i)$ is the mean i-th band reflectance of a unit in the g-th growth state. The iterative procedure uses the training set and current mean and computes a new mean signature which is more representative of the data in the training set.

The initial mean signature is the average of the training vectors whose time components have been simply interpolated over time to describe intermediate growth states. For example, say we have 5 observations, 15 growth states, and $\bar{\alpha}_1(1)$ and $\bar{\alpha}_1(2)$ are the average reflectances in the first band at the first and second observation times. Then $(1;\bar{\alpha}_1(1))$, $(2;\bar{\alpha}_1(1) + \frac{1}{3}(\bar{\alpha}_1(2) - \bar{\alpha}_1(1)))$, $(3;\bar{\alpha}_1 + \frac{2}{3}(\bar{\alpha}_1(2) - \bar{\alpha}_1(1)))$ and $(4;\bar{\alpha}_1(2))$ are in the initial signature u. Figure 3 shows an example of an initial signature of Morton County wheat with 20 growth states. On each iteration we find a monotonic mapping m: $(j,t) \rightarrow g$ which minimizes $\sum_{t=1}^{T} \max_i |x(i,j,t) - u(m(j,t);i)|$ for every sample j. Note that this allows samples at different observation times to map into the same growth state.

At the end of each iteration the mean signature is updated. Define a set A_g as the set of all unit-observation time pairs which are mapped to growth state g. The updated mean signature u' is defined as

$$u'(g,i) = \sum_{(j,t) \in A_g} \frac{x(i,j,t)}{\#A_g}$$

The procedure iterates until it reaches a fixed point. This procedure is implemented in the routine GN1SIG. Figures 4 and 5 show the final growth state mapping and final mean signature created by GN1SIG.

The standard deviation by band and growth state are listed in Table 5.2.2 for the samples mapped into the 20 growth states shown in Figure 4. The average standard deviation is 1.42. This compares with the average sample standard deviation by band-date of 2.88.

The first-order signature is generated from the means $u'(g,i)$. Here (g,α_i) is in the signature if $|\alpha_i - u'(g,i)| < w$. The "signature width" w is chosen to be about twice the magnitude of the average standard deviation of pixel reflectance within the growth stage. Then for each band α_i and growth state g, there is an interval of length $2w$ centered on $u'(g,i)$ of gray tone values in the signature, as shown in Figure 6. We note that, given the degree of variation in sample standard deviation for the growth state bands, a single width for all bands and growth states is probably not best, but is chosen for simplicity. Our second order signature allows for different ranges of gray tones for different bands and growth states.

In the discrimination process, one chooses which bands in the signature to use. Observed gray tone values for a pixel in these bands must fall within these intervals in order for the pixel to be identified as in growth stage g. In the case where more than one growth state identification is possible, the earliest growth state is identified. In order for a pixel to be identified as crop c, each observation must be identified as being in a growth stage for crop c and the growth stages must be chronologically ordered, as mentioned before. One also has the option of limiting the growth stages to a specified

range for each observation time. The discrimination of crop type using a mean first-order signature as input is implemented in the program PHNIDV. If there is more than one crop type to identify, the signatures for each crop type are composed into a single file using the program CPSGFL.

5.2 Second-Order Signature Generation and Discrimination

Second-order signatures are created from the growth state mapping that was made in the last iteration of the first-order mean signature generation procedure. The mapping associates observations of sample pixels with growth states. A three-tuple (g,α_1,α_2) is in the second-order signature of category c for bands b_1,b_2 if there is an observation of a sample pixel with gray tones α_1,α_2 for band b_1,b_2. In our study, the range of gray tone values is 0-31 so that a second-order signature can be represented as a set of 32 x 32 matrices, one for each growth state g. The value of the matrix entry is the α_1-th row and α_2-th column is 1 if (g,α_1,α_2) is in the signature and 0 otherwise. Figures 7 through 11 show the second-order signature the MSS band pair (4,5) created from the first-order mapping shown in Figure 5, using the program GN2SIG.

We have considered that such a signature may be too restrictive to use in the classification process, thus we use a "fill" operation in which neighbors of entries with value "1" are relabeled with a "1". We experimented with the use of several types of "fill" operations on the second-order signature. A "4-fill" is an operation in which the four adjacent entries of a "1" entry are given a 1 value. An "8-fill" is an operation in which the four adjacent and four corner entries of a 1 entry are given the value 1. We also experimented with a "4-4 fill", "4-8 fill", and "8-8 fill" in which "4-fill" and "8-fill" are applied iteratively. Figure 12 illustrates the effect of the various types of "fill" on an isolated 1 entry in the growth state matrix

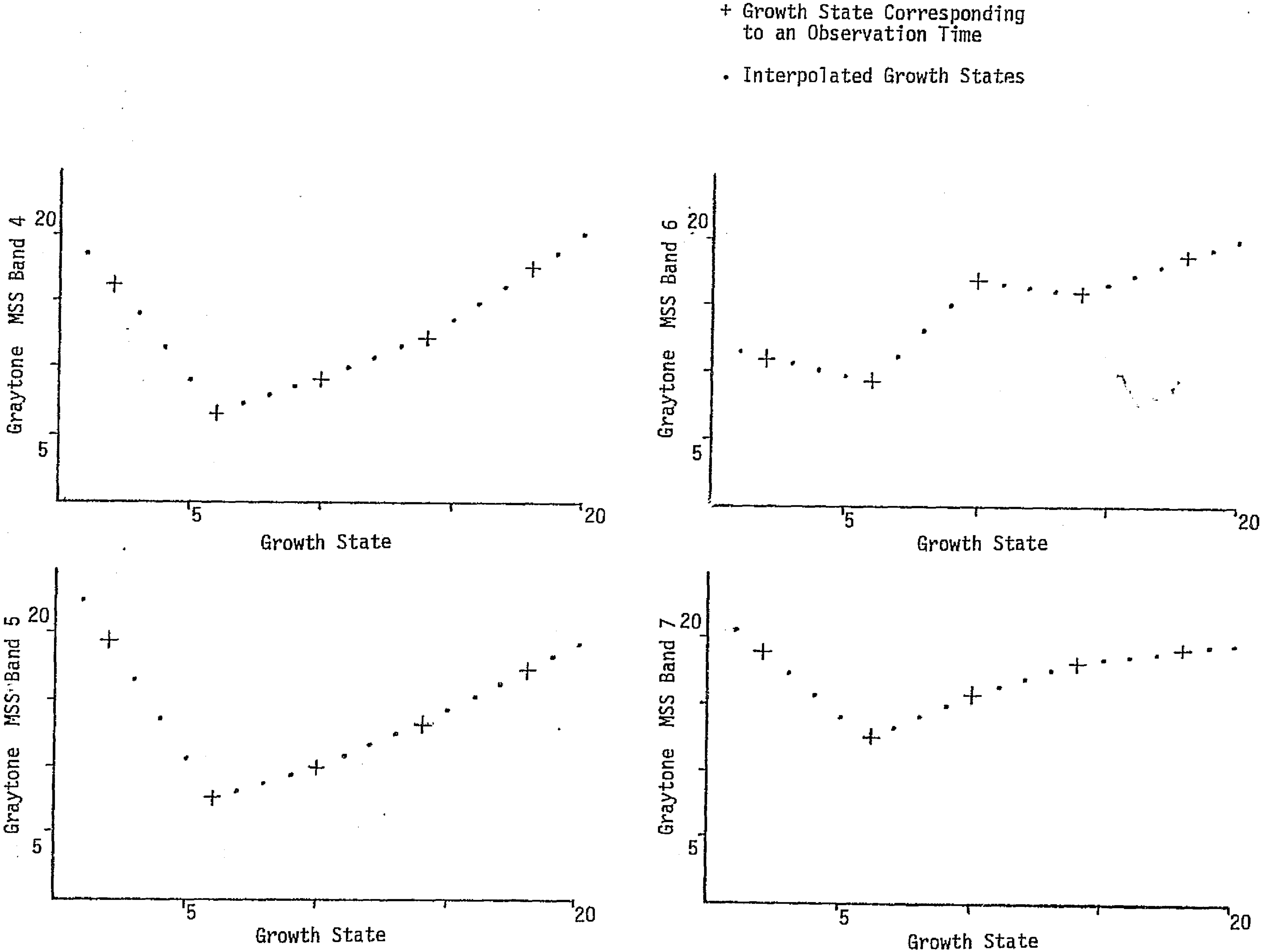


Figure 3. Initial mean wheat signature for Morton County test site

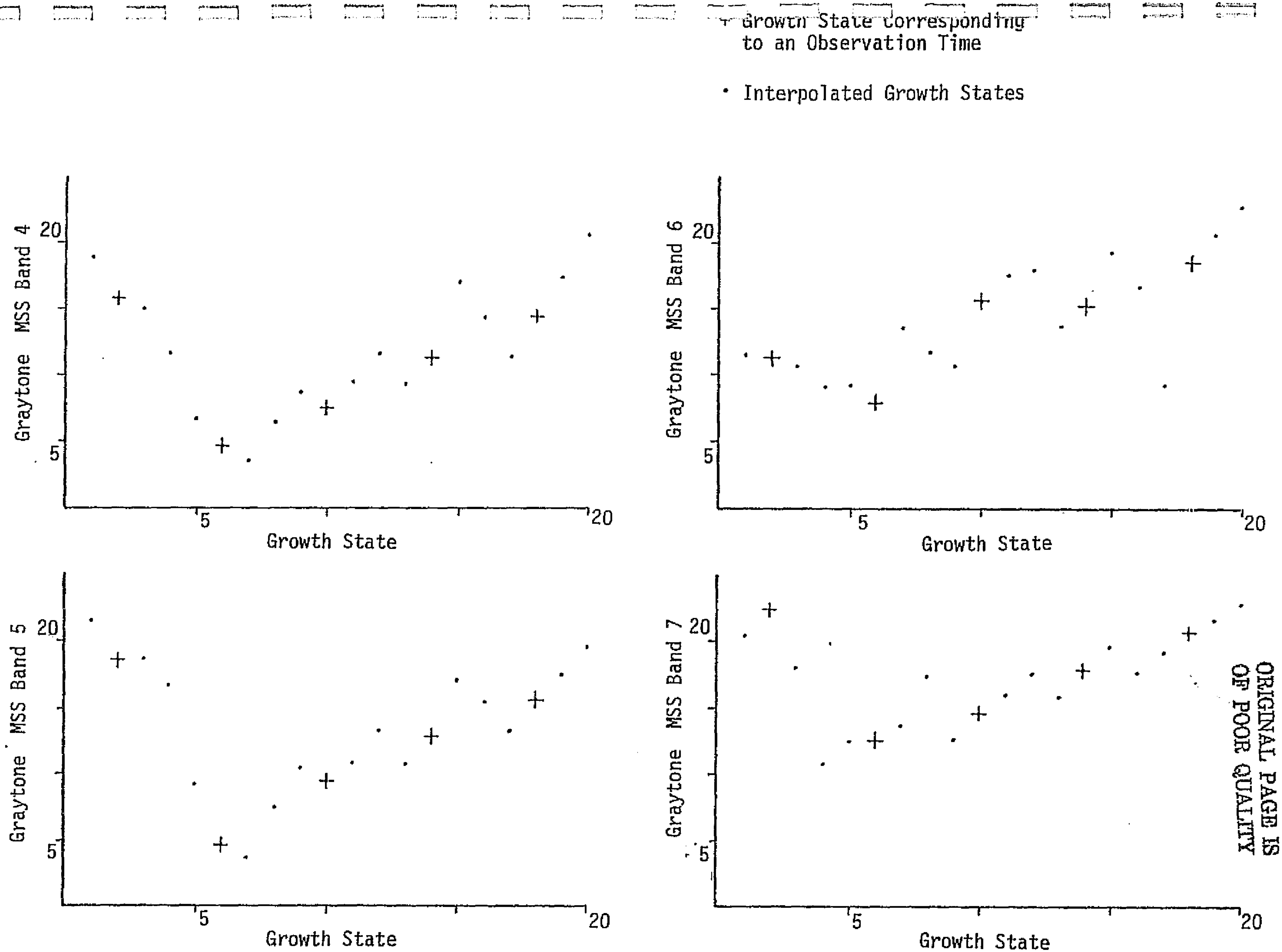


Figure 4. Final mean wheat signature for Morton County test site

MAPPINGS OF THE SAMPLES INTO GROWTH STATES ARE:

SAMP#	GROWTH STATES				
1	1	5	11	18	20
2	1	5	11	18	20
3	1	6	11	16	20
4	3	9	12	15	16
5	3	9	11	15	16
6	1	6	11	16	20
7	1	6	10	14	20
8	1	5	10	14	20
9	3	9	12	16	17
10	1	6	10	14	15
11	3	5	11	14	18
12	1	5	11	16	20
13	1	5	11	16	20
14	1	5	12	16	20
15	1	5	12	16	20
16	1	9	12	15	16
17	3	9	11	14	16
18	3	9	12	16	18
19	1	5	11	18	20
20	1	5	11	16	20
21	1	5	11	16	20
22	1	5	11	18	20
23	2	5	11	15	16
24	1	5	10	14	20
25	1	9	11	12	20
26	3	5	12	16	20
-	3	6	10	14	16
28	3	6	10	13	20
29	1	9	12	14	16
30	2	5	11	14	19
31	3	5	11	16	18
32	3	6	10	14	20
33	2	6	7	8	16
34	1	6	11	12	18
35	1	6	10	14	20
36	4	5	11	13	16
37	1	9	18	19	20
38	4	5	10	14	19
39	3	8	11	12	15
40	1	6	10	18	20
41	4	5	11	12	19
42	4	5	11	16	19
43	1	5	12	16	19
44	1	5	11	16	19
45	1	8	10	14	19
46	1	5	11	16	20
47	1	6	11	14	19
48	1	6	10	14	16
49	1	5	11	12	20
50	1	5	11	14	20
51	4	9	12	13	19
52	2	5	11	14	20
53	1	9	12	16	20
54	1	9	12	16	20
55	1	5	10	12	16
56	1	9	10	15	16
57	1	4	11	14	20
58	3	6	11	14	20
59	3	6	11	16	20
60	4	6	7	13	17
61	4	6	7	13	17
62	3	5	11	18	19
63	3	5	11	16	20
64	3	9	10	13	17
65	1	6	7	8	17
66	5	9	11	12	13
67	3	6	7	16	17
68	4	5	10	13	15
69	2	6	10	14	15
70	3	5	11	13	16
71	3	6	7	8	17
72	2	6	7	9	17
73	2	6	7	8	13
74	2	6	7	8	17
75	1	9	18	19	20
76	2	6	7	9	17
77	2	9	11	19	20
78	3	5	11	14	15
79	2	4	15	16	17
80	1	9	12	18	20
81	2	5	12	18	20
82	3	9	15	16	17
83	2	6	7	13	20
84	2	9	11	18	20
85	3	9	15	16	17
86	2	5	10	18	19
87	3	5	11	12	19
88	3	5	10	14	15
89	3	9	10	16	17
90	2	9	11	14	20
91	2	5	11	16	20
92	3	5	11	16	20
93	4	6	7	8	19
94	2	9	11	14	15
95	2	6	7	8	20
96	3	5	11	12	20
97	2	9	11	18	20
98	4	6	7	8	18
99	2	9	10	18	19
**	3	5	15	16	17
**	3	5	10	14	16
**	3	5	11	16	17
**	4	5	7	14	19
**	1	5	10	15	16
**	4	9	15	16	17
**	3	6	10	13	15
**	3	6	10	13	19
**	4	9	12	14	18
**	2	5	11	13	20
**	2	5	10	13	19
**	2	5	10	13	19
**	4	6	7	9	17
**	2	5	10	14	19
**	2	5	11	14	20
**	2	6	7	13	19
**	2	6	7	13	19
**	2	6	10	13	19
**	2	6	10	13	15
**	1	6	15	16	20
**	2	5	7	13	19

Figure 5. Final growth state mapping output from GNISIG. Each row is a sample pixel number and the growth state mappings for each of the five observation dates.

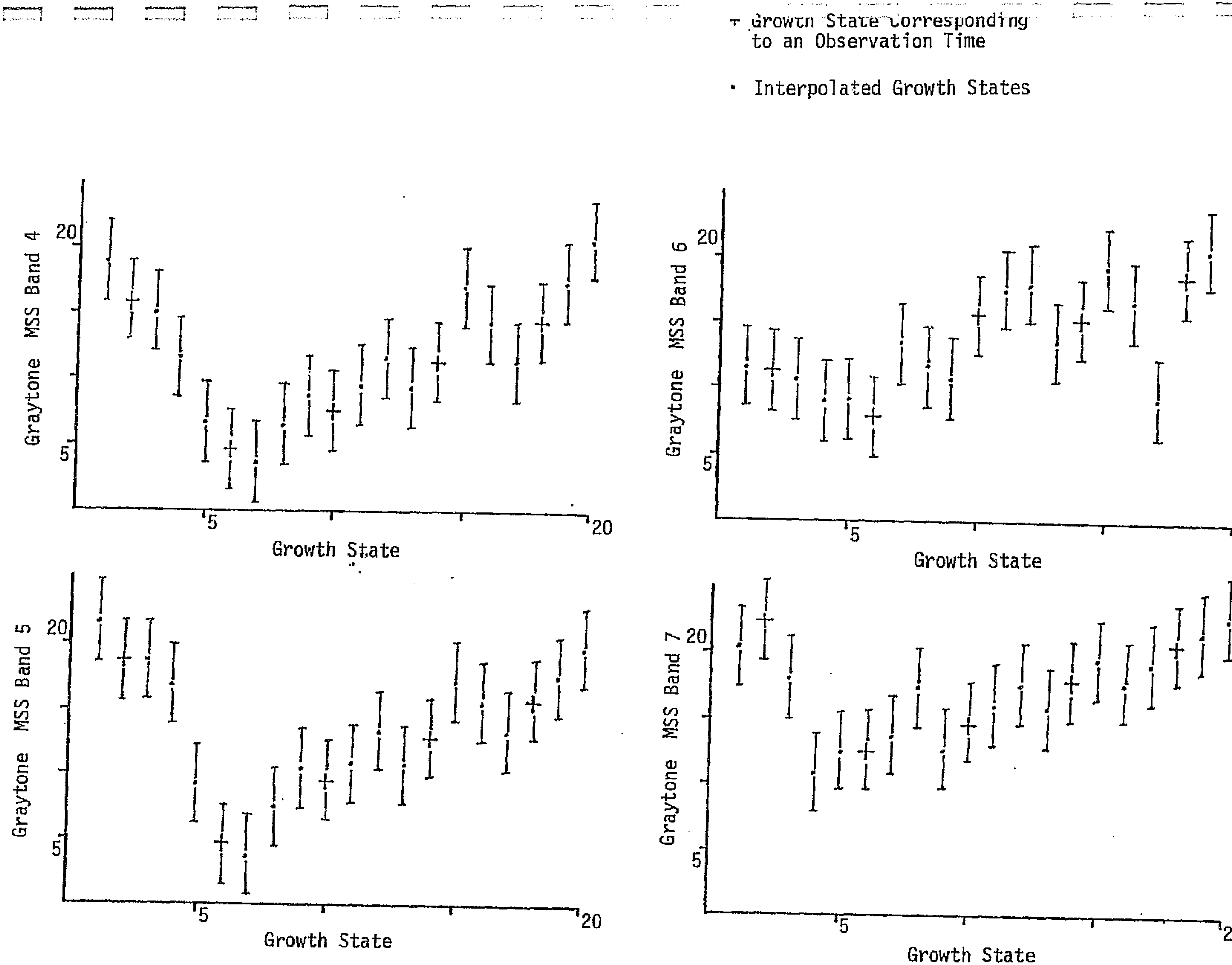


Figure 6. Final mean wheat signature for Morton County test site with tolerance interval set

GROWTH STATE (1)

MSS Band 5: 0 → 31

MSS Band 4: 0 → 31

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000010000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000011100000000
00000000000000000001111000000000
00000000000000000000111100000000
00000000000000000000010100000000
00000000000000000000001000000000
00000000000000000000000100000000
00000000000000000000001100100000
00000000000000000000000000000000
00000000000000000000000010000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (2)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000001110000000000000
00000000000000001010000000000000
00000000000000000011000000000000
00000000000000000011100000000000
00000000000000000101100000000000
00000000000000000011100000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (3)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000001000000000000000
00000000000000001000000000000000
00000000000000000110000000000000
00000000000000001111000000000000
00000000000000000111000000000000
00000000000000000000100000000000
00000000000000000001100000000000
00000000000000000000110000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (4)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000100000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000001000000000000000
00000000000000000000000000000000
00000000000000000110000000000000
00000000000000000000000000000000
00000000000000001110000000000000
00000000000000000001000000000000
00000000000000000000100000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

Figure 7. Second order signature growth states (1-4)

GROWTH STATE (5)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000001000100000000000000000000
00000001100000000000000000000000
00000001110000000000000000000000
00000000111000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (6)

```
00000000000000000000000000000000
00000000000000000000000000000000
01100000000000000000000000000000
01010000000000000000000000000000
00011110000000000000000000000000
00000110000000000000000000000000
00000110000000000000000000000000
00000001000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (7)

```
00000000000000000000000000000000
01000000000000000000000000000000
11000000000000000000000000000000
00111100000000000000000000000000
00011100000000000000000000000000
00001100000000000000000000000000
00000010000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (8)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000010000000000000000000000000
00000001000000000000000000000000
00000010000000000000000000000000
00000000110000000000000000000000
00000000000000000000000000000000
00000000100000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

Figure 8. Second order signature growth states (5-8)

39

OF POOR QUALITY

GROWTH STATE (9)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000001000000000000000000000
00000000111100000000000000000000
00000000001100000000000000000000
00000000011110000000000000000000
00000000001100000000000000000000
00000000000001000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (10)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000100000000000000000000000
00000001111000000000000000000000
00000000011000000000000000000000
00000000011000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (11)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000011100000000000000000000
00000000000010000000000000000000
00000000011111000000000000000000
00000000011110000000000000000000
00000000010010000000000000000000
00000000001001000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (12)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000001000000000000000000000
00000000000000000000000000000000
00000000000011110000000000000000
00000000000110100000000000000000
00000000000110110000000000000000
00000000000000110000000000000000
00000000000000010000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

Figure 9. Second order signature growth states (9-12)

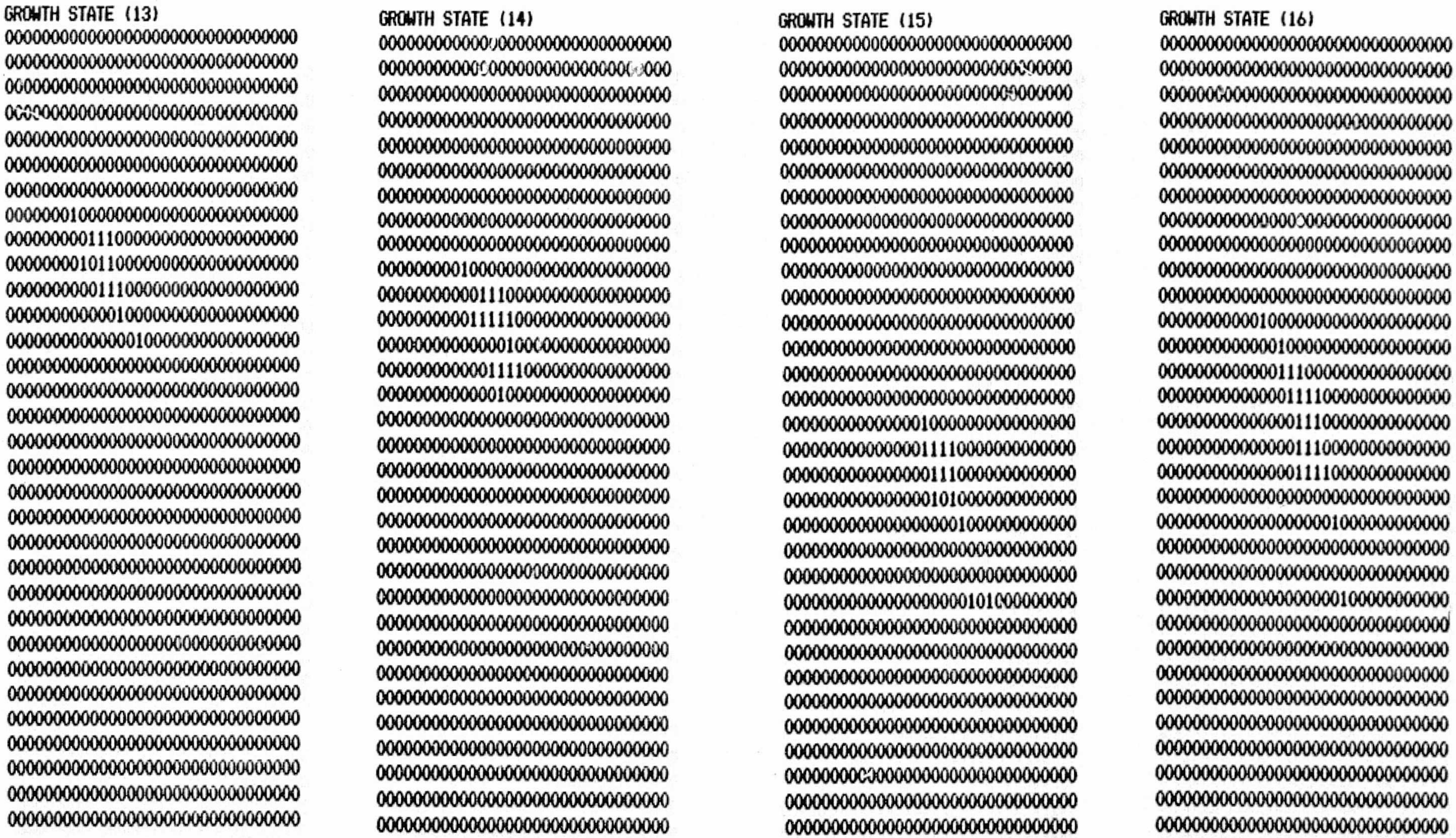


Figure 10. Second order signature growth states (13-16)

41

OF POOR QUALITY

GROWTH STATE (17)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000001000000000000000000000
00000000000110000000000000000000
00000000000000000000000000000000
00000000001110100000000000000000
00000000000010111000000000000000
00000000000000100000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000010000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (18)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000110100000000000000
00000000000000111000000000000000
00000000000000111100000000000000
00000000000000011100000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (19)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000100000000000000
00000000000000000111000000000000
00000000000000000110000000000000
00000000000000001111000000000000
00000000000000000001000000000000
00000000000000000001000000000000
00000000000000000010000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

GROWTH STATE (20)

```
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000001000000000000
00000000000000000000000000000000
00000000000000000100000000000000
00000000000000000111100000000000
00000000000000000011100000000000
00000000000000000111111000000000
00000000000000000011111000000000
00000000000000000000001000000000
00000000000000000000000010000000
00000000000000000000001000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

Figure 11. Second order signature growth states (17-20)

No Fill

0	0	0	0	0
0	0	0	0	0
0	0	1	0	0
0	0	0	0	0
0	0	0	0	0

4-Fill

0	0	0	0	0
0	0	1	0	0
0	1	1	1	0
0	0	1	0	0
0	0	0	0	0

8-Fill

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

4-8 Fill

0	1	1	1	0
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
0	1	1	1	0

4-4 Fill

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

8-8 Fill

1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1
1	1	1	1	1

Figure 12. Types of "fill" used in second-order discrimination

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000010000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000011100000000
00000000000000000001111000000000
00000000000000000000111100000000
00000000000000000000010100000000
00000000000000000000001000000000
00000000000000000000000100000000
00000000000000000000001100100000
00000000000000000000000000000000
00000000000000000000000010000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

NO FILL

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000010000000000000
00000000000000000111000000000000
00000000000000000010000000000000
00000000000000000000011100000000
00000000000000000001111110000000
00000000000000000011111100000000
00000000000000000001111110000000
00000000000000000000111110000000
00000000000000000000011100000000
00000000000000000000001110100000
00000000000000000000011111110000
00000000000000000000001110100000
00000000000000000000000111000000
00000000000000000000000010000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

4FILL

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000111000000000000
00000000000000000111000000000000
00000000000000000111000000000000
00000000000000000000111100000000
00000000000000000011111100000000
00000000000000000011111100000000
00000000000000000011111100000000
00000000000000000001111110000000
00000000000000000000111110000000
00000000000000000000011111110000
00000000000000000000011111110000
00000000000000000000011111110000
00000000000000000000000111000000
00000000000000000000000111000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

8FILL

Figure 13. Effect of spacial fills on a second order signature

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000010000000000000
00000000000000000111000000000000
00000000000000001111100000000000
00000000000000000111011100000000
00000000000000000011111110000000
00000000000000000011111111000000
00000000000000000111111110000000
00000000000000000011111111000000
00000000000000000001111111000000
00000000000000000000111110100000
00000000000000000000011111110000
00000000000000000000111111111000
00000000000000000000011111110000
00000000000000000000001111100000
00000000000000000000000111000000
00000000000000000000000010000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

4-4 fill

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000111000000000000
00000000000000001111100000000000
00000000000000001111100000000000
00000000000000001111111110000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000011111111000000
00000000000000000001111111110000
00000000000000000000111111111000
00000000000000000000111111111000
00000000000000000000111111111000
00000000000000000000011111110000
00000000000000000000001111100000
00000000000000000000000111000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

4-8 fill

```
GROWTH STATE ( 1)
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000001111100000000000
00000000000000001111100000000000
00000000000000001111100000000000
00000000000000001111111111000000
00000000000000001111111111000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000111111111000000
00000000000000000011111111111000
00000000000000000001111111111000
00000000000000000000111111111000
00000000000000000000111111111000
00000000000000000000111111111000
00000000000000000000001111100000
00000000000000000000001111100000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
00000000000000000000000000000000
```

8-8 fill

Figure 14. Effect of spacial fills on a second order signature

45

ORIGINAL PAGE IS OF POOR QUALITY

Date	MSS Band 4	MSS Band 5	MSS Band 6	MSS Band 7
October 23	16.20 3.07	19.38 2.23	11.11 1.82	19.02 3.09
May 9	6.67 2.07	7.52 2.62	9.23 1.44	12.84 2.24
May 27	9.08 3.50	9.97 3.53	17.00 2.19	15.82 2.24
June 14	12.21 3.03	13.25 2.90	15.88 2.35	18.21 2.11
July 2	17.54 3.82	17.32 2.88	18.84 5.12	19.13 5.25

Table 5.2.1. Means and standard deviations of a 120 wheat pixel sample from the Morton County Intensive Test Site.

GROWTH STATE 1 WITH 41 SAMPLES
19.07 21.66 11.88 20.41
1.97 1.39 2.45 1.74

GROWTH STATE 2 WITH 31 SAMPLES
15.68 18.45 11.65 22.48
1.53 1.13 0.48 1.34

GROWTH STATE 3 WITH 33 SAMPLES
15.21 18.61 10.76 17.82
1.79 1.32 0.49 1.40

GROWTH STATE 4 WITH 16 SAMPLES
11.75 16.50 9.00 10.37
2.30 2.60 0.94 2.64

GROWTH STATE 5 WITH 52 SAMPLES
6.85 8.02 9.37 12.46
0.86 0.89 0.90 0.99

GROWTH STATE 6 WITH 37 SAMPLES
4.49 4.43 7.95 12.54
1.39 1.64 1.21 0.95

GROWTH STATE 7 WITH 19 SAMPLES
3.84 3.84 13.74 13.68
1.39 1.72 1.21 1.89

GROWTH STATE 8 WITH 10 SAMPLES
6.90 7.20 11.90 17.50
1.51 0.98 2.02 1.63

GROWTH STATE 9 WITH 31 SAMPLES
8.87 10.32 10.58 12.55
1.13 1.03 1.16 0.94

GROWTH STATE 10 WITH 30 SAMPLES
7.77 9.10 15.87 14.70
0.99 0.91 0.62 1.29

GROWTH STATE 11 WITH 48 SAMPLES
9.71 10.90 17.69 16.02
1.12 1.10 0.85 1.27

GROWTH STATE 12 WITH 24 SAMPLES
12.04 13.33 18.04 17.75
1.34 1.46 1.24 1.33

GROWTH STATE 13 WITH 21 SAMPLES
9.38 10.62 13.38 15.76
1.13 1.46 1.17 1.11

GROWTH STATE 14 WITH 29 SAMPLES
11.41 12.83 15.24 18.14
1.25 1.56 1.16 1.63

GROWTH STATE 15 WITH 21 SAMPLES
17.29 17.24 19.71 19.76
1.93 1.77 2.07 1.41

GROWTH STATE 16 WITH 46 SAMPLES
14.83 15.46 16.59 17.74
1.77 1.47 1.57 1.99

GROWTH STATE 17 WITH 18 SAMPLES
11.33 12.94 9.00 9.06
1.80 1.78 1.94 2.25

GROWTH STATE 18 WITH 20 SAMPLES
14.50 15.40 18.85 20.85
1.12 1.07 1.06 0.85

GROWTH STATE 19 WITH 26 SAMPLES
17.88 17.58 20.69 21.58
1.55 0.84 1.41 1.69

GROWTH STATE 20 WITH 47 SAMPLES
21.02 19.70 22.91 22.91
1.67 1.61 1.51 2.14

Table 5.2.2. The averages (which constitute mean signature) and standard deviations by growth state and MSS band of subsamples of a 120 wheat pixel sample of the Morton County Intensive Test Site. The first row of numbers are band means and the second row of numbers are band standard deviations.

of a second-order signature. Figures 13 and 14 show the effect of the various kinds of fill on the first growth state of the signature shown in Figure 7.

5.3 Bayesian Perspective of Phenological Discrimination

In this section we describe a Bayesian framework for phenological classification of vegetation. We will initially assume that spectral reflectance is a function of vegetation category, vegetation growth state, and calendar time. We will neglect effects of atmospheric haze and geomorphologic soil and moisture variations.

Let G be the set of possible growth states. The growth states will depend on maturity, biomass, percent cover, and height of vegetation. We will assume that the growth states of G are ordered according to the natural maturing cycle which the vegetation undergoes. Let $\{t_1,\ldots,t_N\}$ be the set of observation times. The times in the set T are naturally ordered by the relation earlier than or later than. Let R be the set of possible reflectance values and $B = \{1,2,\ldots,M\}$ be the set of M wavelengths bands of spectral reflectance that can be observed by the sensor.

Let x be a spectral reflectance vector of vegetation category c in phenological growth stage g at calendar time. We denote the probability of observing (x,c,g) at a given calendar time t by $P(x,c,g|t)$.

For multi-temporal multi-spectral data, the probability function of spectral reflectance vectors $x_1,\ldots,x_N$ coming from a small area ground patch of categories $c_1,\ldots,c_N$ in phenological growth stages $g_1,\ldots,g_N$ at calendar times $t_1,\ldots,t_N$ respectively, is denoted by

$$P(x_1,\ldots,x_N,c_1,\ldots,c_N,g_1,\ldots,g_N \mid t_1,\ldots,t_N)$$

To determine a Bayes rule, the probability $P(x_1,\ldots,x_N,c_1,\ldots,c_N \mid t_1,\ldots,t_N)$ must be computed. Now

$$P(x_1,\ldots,x_N,c_1,\ldots,c_N \mid t_1,\ldots,t_N) =$$

$$\sum_{g_1}\cdots\sum_{g_N} P(x_1,\ldots,x_N,c_1,\ldots,c_N,g_1,\ldots,g_N \mid t_1,\ldots,t_N)=$$

$$\sum_{g_1}\cdots\sum_{g_N} P(x_1,\ldots,x_N \mid c_1,\ldots,c_N,g_1,\ldots,g_N,t_1,\ldots,t_N)$$

$$\cdot\ P(c_1,\ldots,c_N,g_1,\ldots,g_N \mid t_1,\ldots,t_N)$$

We assume that the reflectance x depends only on crop type c and growth stage g so that

$$P(x_1,\ldots,x_N \mid c_1,\ldots,c_N,g_1,\ldots,g_N,t_1,\ldots,t_N) = \prod_{n=1}^{N} P(x_n \mid c_n,g_n,t_n)$$

Likewise, we assume that vegetative growth is a Markov process depending on time and vegetation category alone so that

$$P(g_1,\ldots,g_N \mid c_1,\ldots,c_N,t_1,\ldots,t_N) = \prod_{n=1}^{N} P(g_n \mid c_n,c_{n-1},t_n,t_{n-1})$$

and

$$P(c_1,\ldots,c_N,g_1,\ldots,g_N \mid t_1,\ldots,t_N) =$$

$$P(g_1,\ldots,g_N \mid c_1,\ldots,c_N,t_1,\ldots,t_N)\ P(c_1,\ldots,c_N \mid t_1,\ldots,t_N) =$$

$$\left[\prod_{n=1}^{N} P(g_n \mid c_n,c_{n-1},g_{n-1},t_{n-1},t_n)\right]\cdot P(c_1,\ldots,c_N \mid t_1,\ldots,t_N)$$

so that the probability for observed categories and multi-spectral reflectances is [*]:

$$P(x_1,\ldots,x_N,c_1,\ldots,c_N \mid t_1,\ldots,t_N) = \sum_{g_1} P(x_1 \mid c_1,g_1)\, P(g_1 \mid c_1,t_1)$$

$$\cdot\sum_{g_2} P(x_2 \mid c_2,g_2)\, P(g_2 \mid c_1,c_2,g_1,t_1,t_2) \qquad [*]$$

$$\cdots\sum_{g_N} P(x_N \mid c_N,g_N)\, P(g_N \mid c_{N-1},c_N,g_{N-1},t_{N-1},t_N)$$

$$\cdot P(c_1,\ldots,c_N \mid t_1,\ldots,t_N)$$

In theory, the formula just derived could be used to determine a Bayes rule in the usual way. In practice, there are too many distributions to estimate and too many calculations to do to calculate the required probabilities. However, because the required probability has the form of a product, if any probability in the product is zero, then the product must be zero. And a Bayes rule would never make an assignment to a category with a zero probability. This fact can be utilized to make an efficient table look-up rule which uses vegetation phenology just by storing in the table(s) those regions in measurement space having non-zero probability.

The astute reader will undoubtedly wonder why such a decision scheme has any chance of working at all. Why can it not be that any spectral observation vector is possible for many growth stages for most categories? The reason that this is not possible is empirical. The probability distributions are conditioned by crop growth state so that the resulting conditioned probability distributions are expected to have much smaller variances than the usual unconditioned ones. The conditioned ones, are therefore, much more peaked.

5.3.1 A Mathematical Description of Classification Using Phenological Vegetation Signatures and Prior Constraints

Given observation times $t_1,\ldots,t_N$ during which a small area ground patch is observed, in the previous section we derived a formula for the probability of a small area ground patch having corresponding vegetation types $c_1,\ldots,c_N$ with respective spectral reflectance vectors $x_1,\ldots,x_N$. In this section we will show how this kind of representation for the probability can be used to define vegetation signatures and a classification method which can then be used to recognize vegetation type and vegetation growth state in a structural pattern recognition manner which is implementable as a table look-up rule.

For simplicity of discussion we will assume that for the observation times $t_1,\ldots,t_N$, the small area ground patch being observed does not change vegetation type and that the vegetation itself matures in a normal manner. We will also allow for the possible use of prior information which would indicate that at given observation times only certain growth states for the vegetation category are reasonable ones. Such prior constraints can come from historical crop calendar information, perhaps combined with a vegetation growth model that uses local weather temperature and moisture information.

Before we define prior constraints vegetation signature, we need to discuss some notational conventions. Let G be the set of possible growth states for the vegetation category. The growth states will depend on the maturity, biomass, percent cover, and height of the vegetation. We will assume that the growth states of G are ordered according to the natural maturing cycle which the vegetation undergoes. Let T be the set of observation times. The times in the set T are naturally ordered by the relation earlier than or later than. Let R be the set of possible reflectance values and $B = \{1,2,\ldots,M\}$

be the set of M wavelengths bands of spectral reflectance that can be observed by the sensor. Each spectral return vector x is a member of the set R^M. The m^{th} component of x is the spectral return using the m^{th} wavelength band of B.

If the vegetation category does not change over the period of observation so that $c_i = c$ for $i = 1,2,\ldots,N$, then the probability [*] derived in the last section is [**]:

$$P(x_1,\ldots,x_N,c \mid t_1,\ldots,t_N) =$$

$$\left\{ \prod_{n=1}^{N} \left[\sum_{g_n} P(x_n \mid c,g_n)\, P(g_n \mid c,g_{n-1},t_{n-1},t_n)\right]\right\} \cdot P(c) \qquad [**]$$

A necessary condition for a Bayes rule to assign the multi-temporal, multi-spectral vectors $x_1,\ldots,x_N$ to category c is for $P(x_1,\ldots,x_N,c \mid t_1,\ldots,t_N)$ to be non-zero. Since this joint probability is a product, if the joint probability is non-zero, then every term of the product must be greater than zero. This means that for each n:

$$\sum_{g_n} P(x_n \mid c,g_n)\, P(g_n \mid c,g_{n-1},t_{n-1},t_n) > 0$$

The product in each term of the above sum if non-zero iff $P(x_n \mid c,g_n)$ and $P(g_n \mid c,g_{n-1},t_n,t_{n-1})$ are both non-zero. The term $P(x_n \mid c,g_n)$ is non-zero iff the spectral reflectance vector x_n is possible for vegetation category c in growth state g_n. The term $P(g_n \mid c,g_{n-1},t_{n-1},t_n)$ is non-zero iff the crop calendar practices of the region being observed allow vegetation of category c to be in growth state g_n at time t_n and the rate of growth of vegetation type c is such that growth g_n can be reached from state g_{n-1} in the time period from t_{n-1} to t_n.

The set S is called a signature for a category if it contains those data vectors whose components are spectral reflectances having non-zero probability for a growth state of a category. We can formalize a definition of K-th order signature in a way that allows us to consider K-dimensional data vectors. Let M specify band wavelengths. Let $x = (\alpha_1,\ldots,\alpha_M) \in R^M$ be a full set of M observed reflectances and denote by $(b_1,\ldots,b_K) \in B^K$ a subset of $B' \subseteq B^K$. The K-th order signature is defined with respect to only those K-tuples of bands in B'. The <u>K-th order signature</u> of a category C $S \subseteq G \times (R \times B)^K$ consists of all $(2K + 1)$ tuples of growth state, reflectance, band, . . ., reflectance, and band whose conditional probability is greater than zero

$$S = \{(g,(r_1,b_1),\ldots,(r_k,b_k)) \in G \times (R \times B)^K \mid \text{for some } (b_1,\ldots,b_k) \in B',\ P_{b_1,\ldots,b_k}(r_1,\ldots,r_k \mid g,C) > 0\}$$

where the pair (r_1,b_1) denotes reflectance value corresponding band wavelength so that $r_i = \alpha_{b_i}$.

In an analogous way, a <u>K-th order observation relation</u> $\theta \subseteq T \times (R \times B)^K$ consists of all those $(2K + 1)$ tuples of observation time, reflectance, band, . . ., reflectance, and band which have been measured.

$$\theta = \{(t,(r_1,b_1),\ldots,(r_k,b_k)) \in T \times (R \times B)^K \mid \text{for some } (b_1,\ldots,b_k) \in B' \text{ and for some } n,\ t = t_n \text{ and observed reflectance were } r_i \text{ on bands } b_i \text{ for } i = 1,2,\ldots,K\}.$$

At each observation time at most one reflectance value is measured for each band. (There may be none if there is missing data). Note that the only K-tuples of reflectance bands used for observations are those K-tuples in B'.

The set C of prior constraints relating growth states to observation times and growth states at earlier times is

$$C = \{(t_1,g_1,t_0,g_0) \text{ in } (T \times G)^2 \mid P(g_1 \mid t_1,t_0,g_0) > 0 \text{ and } t_1 > t_0\}$$

To determine if an observation θ requires us to reject a vegetation category (that is, determine if [**] is non-zero), we will determine if for every n, (1) there exists a growth state g_n such that $P(x_n \mid c,g_n)$ is non-zero, and (2) if the g_n is such that $P(g_n \mid c,g_{n-1},t_{n-1},t_n)$ is non-zero.

Let H be a subset of T x G so that H associates observation times with growth states. We define the relation composition of θ with H, written $\theta \circ H$ by

$$\theta \circ H = \{(g,(r_1,b_1),\ldots,(r_k,b_k)) \text{ in } G \times (R \times B)^K \mid \text{for some } t \in T,\ (t,(r_1,b_1),\ldots,(r_k,b_k)) \in \theta \text{ and } (t,g) \in H\}.$$

If $\theta \circ H$ is not a subset of S, then (1) is not satisfied. If $\theta \circ H$ is a subset of S and K = M and H is defined everywhere on T, then (1) is satisfied. If H x H is a subset of C and H is defined everywhere on T, then (2) is satisfied.

Given θ and S, let us find H so that $\theta \circ H$ is a subset of S and H x H is a subset of C in the case where

$$C = \{(t_1,g_1,t_0,g_0) \in (T \times G)^2 \text{ if } t_1 > t_0 \text{ implies } g_1 > g_0 \text{ and } (t_1,g_1) \text{ and } (t_0,g_0) \text{ in } C'\}$$

where

$$C' = \{(g,t) \mid P(g|t) > 0\}$$

That is, growth states are constrained to be chronologically ordered in time and consistent with observation times.

The table look-up implementation for finding H is as follows. For each K-tuple $(b_1,\ldots,b_K)$ of bands in B' there is a table $T(b_1,\ldots,b_K)$, which gives lists of possible growth states for values of reflectances in bands $b_1,\ldots,b_K$. These tables together comprise the K-th order signature S. There is a table C' listing possible growth states for a given observation times. The implementation works as follows.

Given θ in $T \times (R \times B)^K$, the existence of a function satisfying (1) and (2) is an easy matter to ascertain. Define $F(b_1,\ldots,b_K)$ by:

$$F(b_1,\ldots,b_K) = \{(t,g) \in C' \mid \text{for some } (r_1,\ldots,r_K) \text{ in } R^K, \\ (t,r_1,b_1,\ldots,r_K,b_K) \in \theta \text{ and } (g,(r_1,b_1),\ldots,(r_K,b_K)) \in S\}$$

Then with the properties of θ already mentioned, the proposition at the end of this section states that any $H \subseteq C'$ satisfying $\theta \circ H \subseteq S$ must be contained in $\bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,b_K)$ and furthermore, the composition

$\theta \circ \bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,b_K)$ must be contained in S.

This implies that we can determine the existence of a function satisfying (1) and (2) by construction. First construct the relation W in C' defined by

$$W = \bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,b_K)$$

Then construct a monotonic part H of V in W. If this H associates a growth state for each observation time, then H is a function satisfying (1) and (2).

Suppose t_1 is the first observation time. Using the table C' we retrieve a set of possible growth states G_1 and we check growth states in G_1 against observed reflectances until we find the earliest growth state consistent with the observed reflectances. We check a growth state in G_1 as follows: For

each K-tuple of bands in B' we enter the corresponding observed reflectances at t_1 into the table $T(b_1,\ldots,b_K)$ and get back a set of growth states. If each such set contains the growth state we are considering, the growth state is consistent with the observed reflectances. At time t_2, we retrieve a set of possible growth states and intersect with the set of possible growth states later than the earliest consistent growth state for t_1 to get G_2. Then find the earliest growth state in G_2 which is consistent with the observed reflectances at time $t_2,\ldots,\ldots,$ and so on for each observation time.

We will now state and prove the proposition mentioned earlier in this section.

Proposition 1

Let $\theta \subseteq T \times (R \times B)^K$, $S \subseteq G \times (R \times B)^K$, $H \subseteq C' \subseteq T \times G$, and $B' \subseteq B^K$. Define $F(b_1,\ldots,b_K)$ as follows:

$$F(b_1,\ldots,b_K) = \{(t,g) \in C' \mid \text{for some } (r_1,\ldots,r_K) \in R^K, \\ (t,r_1,b_1,\ldots,r_K,b_K) \in \theta \text{ and } (g,r_1,b_1,\ldots,r_K,b_K) \in S\}$$

Suppose we have one set of measurements per observation for one small area of ground, so that for each $t \in T$ and $(b_1,\ldots,b_K) \in B'$, there exists exactly one $(s_1,\ldots,s_K) \in R^K$ such that $(t,b_1,s_1,\ldots,b_K,s_K) \in \theta$. Then $H \subseteq \bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,$ if and only if $\theta \circ H \subseteq S$.

Proof

Suppose $H \subseteq \bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,b_K)$. Let $(g,r_1,\beta_1,\ldots,r_K,\beta_K) \in \theta\circ H$. Then there exists a $t \in T$ such that $(t,r_1,\beta_1,\ldots,r_K,\beta_K) \in \theta$ and $(t,g) \in H$. Now $(t,r_1,\beta_1,\ldots,r_K,\beta_K) \in \theta$ implies $(\beta_1,\ldots,\beta_K) \in B'$. Then $(t,g) \in H$ implies $(t,g) \in$

$\bigcap_{(b_1,\ldots,b_K) \in B'} F(b_1,\ldots,b_K)$; thus $(t,g) \in F(\beta_1,\ldots,\beta_K)$.

Since $(t,g) \in F(b_1,\ldots,b_K)$, there exists some $(s_1,\ldots,s_K) \in R^K$ such that $(t,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta$ and $(g,s_1,\beta_1,\ldots,s_K,\beta_K) \in S$. But $(t,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta$ and $(t,r_1,\beta_1,\ldots,r_K,\beta_K) \in \theta$ implies $s_i = r_i$, $i = 1,\ldots,K$. So we must have $(g,r_1,\beta_1,\ldots,r_K,\beta_K) \in S$ and $\theta \circ H \subseteq S$.

Suppose $\theta \circ H \subseteq S$. Let $(t,g) \in H \subseteq C'$. Let $(\beta_1,\ldots,\beta_K) \in B'$. Since there is one set of measurements for t, there exists $(s_1,\ldots,s_K) \in R^K$ so that $(t,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta$. Then $(t,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta$ and $(t,g) \in H$ implies $(g,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta \circ H \subseteq S$. Now $(t,g) \in C'$, $(t,s_1,\beta_1,\ldots,s_K,\beta_K) \in \theta$ and $(g,s_1,\beta_1,\ldots,s_K,\beta_K) \in S$ imply $(t,g) \in F(\beta_1,\ldots,\beta_K)$. Then
$H \subseteq \bigcap_{(\beta_1,\ldots,\beta_K) \in B'} F(\beta_1,\ldots,\beta_K)$.

5.3.2 <u>Table Look-Up Rule Implementation (First-Order and No Prior Constraints)</u>

In this section we specialize the implementation discussed in Section 5.3.1 for the first-order signature case with no prior constraints on growth states. A sufficient condition for $\sum_{g_n} p(x_n|c_n,g_n)p_{t_n}(g_n|c_n)$ to be zero is for $p(x_n|c_n,g_n) = 0$ for all values of g_n. Let x be a K-dimensional spectral reflectance observation. A sufficient condition for $p(x|c,g) = 0$ for all growth values of g is for there to be no phenological growth stage g which gives a positive marginal conditional probability for each component of the observed reflectance x. Let $P_{1\ldots K}(\alpha_1,\ldots,\alpha_K|c,g)$ be the probability of observing the K spectral band reflectance $(\alpha_1,\ldots,\alpha_K)$ from a vegetation of type c in growth state g. Let $P_k(\alpha_k|c,g)$ be the marginal probability of observing spectral reflectance α_K from band K given vegetation type c and growth stage g. Then a sufficient condition for $P_{1\ldots.K}(\alpha_1,\ldots,\alpha_K|c,g) = 0$ is for $P_K(\alpha_K|c,g) = 0$ for some spectral band k. If there is no phenological growth state which gives a positive marginal conditional probability for each component of the observed spectral reflectance $(\alpha_1,\ldots,\alpha_K)$, then $\bigcap_{k=1}^{K} \{g|P_k(\alpha_k|c,g) > 0\} = \emptyset$. This leads to the following criteria for eliminating category assignments which a Bayes rule would also eliminate.

For a given $\varepsilon \geq 0$, define the table by $R(k,\alpha,c) = \{g | P_k(\alpha | c,g) \geq \varepsilon\}$. Suppose multi-temporal multi-spectral returns of $(\alpha_{11},\ldots,\alpha_{1K})$, $(\alpha_{21},\ldots,\alpha_{2K}),\ldots,(\alpha_{N1},\ldots,\alpha_{NK})$ are observed for calendar times $t_1,\ldots,t_N$. Then if $\bigcap_{k=1}^{K} R(k,\alpha_{nk},c) \neq \emptyset$ for some n, a Bayes rule could not make the assignment to category c. If $\bigcap_{k=1}^{K} R(k,\alpha_{nk},c^*) \neq \emptyset$ for all n, and for every $c \neq c^*$, $\bigcap_{k=1}^{K} R(k,\alpha_{nk},c) = \emptyset$ for some n, then a Bayes rule must make the assignment to the unique category c*.

5.3.3 Example

An example easily illustrates the first-order table look-up idea graphically. Figure 15 shows graphs for the tables $R(k,\alpha,c)$. A square blacked in for coordinates (g,α) means that for the corresponding spectral value α, the phenological growth stage g belongs to the table R. Suppose that there are two spectral wavelengths band 1 and band 2, two categories, and two times at which observations are taken. Let the spectral observation for time 1 be (9,10) and the spectral observation for time 2 be (3,6). Examining the tables for category 1, we have

$$R(1,9,1) = \{3,5,6,7\}$$

$$R(2,10,1) = \{0,1,2,3,17,18,19\}$$

$$R(1,9,1) \cap R(2,10,1) = \{3\}$$

This means that the only time the observation (9,10) could occur from category 1 is during phenological growth stage 3. Examining the tables for category 2, we have

$$R(1,9,2) = \{5,6,7,13,14\}$$

$$R(2,10,2) = \{0,1,7,8,18,19\}$$

$$R(1,9,2) \cap R(2,10,7) = \{7\}$$

This means that the only time the observation (9,10) could occur from category 2 is during phenological growth stage 7. So after the first spectral observation, both categories are still possible.

Now consider the second observation (3,6). By the tables

$$R(1,3,1) = \{13,14\}$$
$$R(2,6,1) = \{6,7,8,9,13,14\}$$
$$R(1,3,1) \cap R(2,6,1) = \{13,14\}$$

This means that spectral observation (3,6) is possible for category 1 only during phenological growth stages 13 and 14.

By the tables

$$R(1,3,2) = \{0,1\}$$
$$R(2,6,2) = \{11,12\}$$
$$R(1,3,2) \cap R(2,6,2) = \emptyset$$

This means that there is no phenological growth stage for category 2 which yields the spectral observation (3,6). The conclusion, therefore, is that the small area ground patch having early spectral return of (9,10) and later spectral return of (3,6) must be an area of vegetation category 1 observed during its 3 and 13 or 14 phenological growth stages.

If instead of the intersection $R(1,3,2) \cap R(2,6,2) = \emptyset$, we had $R(1,3,2) \cap R(2,6,2) = \{4,6\}$, category 2 would be eliminated because the spectral reflectance it has at a late calendar time match possible a spectral reflectance for category 2 only at early phenological growth states 4 or 6. Later calendar times must correspond to later phenological growth states.

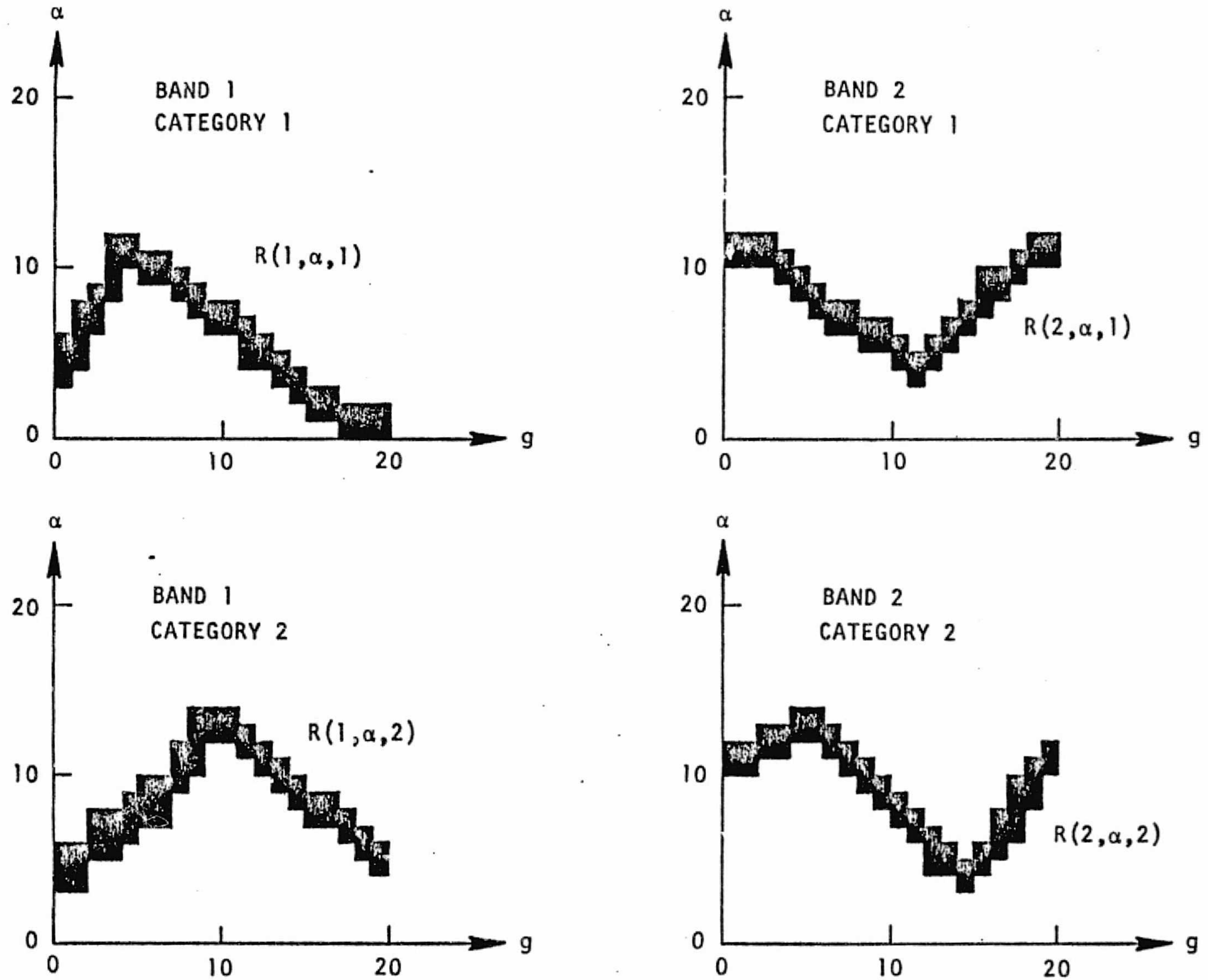


Figure 15. Figure 15 shows graphically the tables $R(b,\alpha,c)$. A square blacked in for coordinates (g,α) means that for the corresponding α, the phenological growth stage g belongs to the table R. A growth stage $g \in R(b,\alpha,c)$ if and only if $P_b(\alpha|g,c) > \varepsilon \geq 0$ for some specified value of G.

5.4 Madison County, Iowa Phenological Discrimination Results

Two subimages of the Madison County area were created and preprocessed, as mentioned in section 3.1. One subimage contains the Scott Township area, with 7 corn fields of ground truth, and will be referred to as the Scott image. The other subimage contains the Douglas Township area with 5 corn fields, 3 soybean fields, and the town of Winterset, and will be referred to as the Douglas image.

Identification of corn on the Douglas image was initially very poor. First and second order corn signatures were created using a training set of 58 randomly chosen pixels of corn on the Scott image. Agricultural areas and non-agricultural areas were separated well, but corn and soybeans were confused. First order discrimination between corn and soybeans (as non-corn), using MSS Bands 4, 5, 6, and all observation times was not significantly different from random labeling. Second order discrimination using MSS Band pair (4,5) was somewhat better, but still very poor.

The multi-temporal multi-band observations of corn pixels in a sample from the Scott image were compared with the observations of corn in a sample from the Doulgas image. It was noted that there were significant differences between the two samples. Reflectance values in all four MSS Bands are higher for Douglas corn on the May 27 observation. This may be due to a soil color difference between the two areas, as the corn is just emerging at this time of the year. Also, MSS Bands 6 and 7 reflectances are consistently higher for Douglas corn than for Scott corn on all four observation dates. The Douglas corn was more variable looking than the Scott corn. Because of these differences between corn in the two areas, it was decided that the poor classification results were due to training sample inadequacy.

COL = ASSIGNED CAT
ROW = TRUE CAT

	RESERVED DEC	CORN	TOTAL
UNKNOWN	23238	38796	62034
CORN	13	356	369
SOY	45	17	62
TOWN	535	1	536
TOTAL	23831	39170	63001

Table 5.4.1 Contingency table for corn/non-corn discrimination in Douglas Township. Number growth state restrictions specified.

COL = ASSIGNED CAT
ROW = TRUE CAT

	RESERVED DEC	CORN	TOTAL
UNKNOWN	40557	21477	62034
CORN	41	328	369
SOY	62	0	62
TOWN	535	1	536
TOTAL	41195	21806	63001

Table 5.4.2 Contingency table for corn/non-corn discrimination in Douglas Township. Growth restrictions used in the discrimination process.

A first order, 16 growth state mean signature was generated using 60 corn pixels from the Douglas image and 53 corn pixels from the Scott image, combined into a sample of 113. Discrimination using this mean signature was much better. Classification results with a signature width of 2.5 and using MSS Bands 4, 5, and 6 on all dates are shown in Table 5.4.1. Discrimination with a signature width of 3.0 and restricting growth state assignments to between (and including) growth states 1 and 4 for the first observation between growth states 5 and 8 for the second observation time, between growth states 7 and 12 for the third observation time. and between states 13 and 16 for the fourth observation time during the classification process gave very good results, as shown in Table 5.4.2. Nearly all (89%) of the ground truth corn was identified and no soybean pixels were falsely identified as corn.

The results show the importance of an adequate training sample. They also show that limiting the range of possible growth states for each observation time can reduce errors of commission significantly.

5.5 Identification of Wheat in Morton County Using Phenological Discrimination Methods

An extensive investigation of the use of phenological discrimination was carried out using the Morton County image. The phenological discrimination procedure involves a number of choices for the user. The procedure involves two steps: (1) Creation of the signature mean in the case of first-order discrimination or the "unfilled" signature for second-order discrimination and (2) Identification using the signature created in Step 1. The effects of the choices on the quality of classification will be discussed. The validity of use of our dynamic programming method for creation of first-order mean signatures, GN1SIG, is also investigated.

5.5.1 A Discussion of First-Order Phenological Results

Consider the two steps in the first-order discrimination procedure. In the first step (GN1SIG), the user chooses an input sample to train the signature and the number of growth states to be characterized in the signature. In the identification step (PHN1DV), the user chooses the "signature width" and which MSS Band/observation date combinations to use. The choice of "signature width" is critical, especially when one is identifying only one crop class. The larger the "signature width" the more pixels will be identified as in the crop class. The percent correct identification will increase with "width" but at the cost of increased false identification. In the identification step, the user also has the option of specifying a range of allowed growth states for each observation time. A good choice of these growth state restrictions effectively cuts down on the number of false classifications, without much reduction in the rate of correct classification.

Sample adequacy was investigated by comparing the discrimination results with no growth state restrictions using a sample of 35 wheat averages and several random samples of individual pixels. The results shown in Table 5.5.1 are somewhat eratic. It seems that a sample of around 100 pixels (about 2.5% of the ground truth wheat) is of adequate size as discrimination is not much better for a sample of twice that size.

We have performed 4 identifications of wheat with signatures having 5, 10, 20, and 36 growth states. This is a range of one to seven growth states per observation time, since w ehave five observations of the Morton County test site. The general shape of the mean signatures with differing numbers of growth states is the same. Our best discrimination was with a 36 growth state signature (see Table 5.5.5) with a width of 3.25. Using this signature and all

observation dates, the results were 83% correct identification of ground truth wheat and 4% false identification. With a 5 growth state signature with a width of 6.0, the corresponding figures were 79% and 13%. The improved discrimination shows the usefulness of modeling several growth states per observation time. Figures 16-20 show the growth state identification on each date for pixels that were classed as wheat with the 36 growth state signature.

The number of MSS Bands needed for accurate identification was investigated. Most of our testing of the first-order discrimination procedure has been done using MSS Bands 4, 5, and 6. However, it has been found that MSS Bands 4 and 5 are sufficient for good wheat identification. Adding MSS Band 7 reduced correct classification significantly. It was thought that perhaps MSS Bands 5 and 7 were more useful for phenological discrimination of wheat, because they have often been most useful in other discrimination procedures in classifying an agricultural scene. The identification of wheat with MSS Bands 5 and 7 using the first-order phenological method turned out not to be as good as with MSS Bands 4 and 5.

The possibility of accurate wheat identification with a single channel of information per observation time was investigated. The phenological method of discrimination is a process of identifying growth stages. It seemed likely, then, that a single measure, indicating greenness of the pixel at the observation times, would be sufficient for identification of the crop. The four MSS Band values for each observation date were transformed into Kauth greenness (Kauth, 1976) scaled to fit in the 0-31 integer value range:

$$KG = .514(-.290\ MSS4 - .562\ MSS5 + .600\ MSS6 + .491\ MSS7) + 13.6$$

An 'SIF' image was created with 25 bands of numerical information: the four MSS Bands and KG for each of the five observation dates. A first-order, five-band mean signature of 20 growth states was created using this image. Wheat was identified using only the Kauth greenness band in the signature and restricting identification of growth states in the procedure to 1-4, 5-8, 9-12, 13-16, and 17-20 for the first, second, third, fourth, and fifth observation times. The identification process was run several times using signature tolerance "widths" ranging from 1.0 to 2.25 and compared to several runs using MSS Bands 4, 5, and 6. Wheat identification using KG was not as good as identification with two or three MSS Bands.

Good wheat identification depends on the proper choice of growth state restrictions, especially if a subset of observation times are used. A description of a run using only two observation times will illustrate this. The growth state identifications with a 36 growth state signature allowed were states 1-5 for observation time 1 and states 10-12 for observation time 2. The narrow choice of growth states allowed for the second observation time, May 9, is important because winter wheat is mainly distinguished from other crop types because it is green on the May 9 date. The growth states 10-12 in the signature had low gray tone values in MSS Band 5, which shows that they correspond to green states. Eighty-one percent of the ground truth wheat was identified and 5 percent of the non-wheat cells were falsely labeled wheat.

The best choice of observation times was October 23 and May 9 for first-order discrimination of wheat. The best single observation time turned out to be May 9, as expected (see Table 5.5.2) because May 9 is when winter wheat is green, in constrast to other crops. The October 23 observation turned out to be the best addition to the May 9 observation (see Table 5.5.3). A third observation improved results significantly only when wheat was broken into

two categories--quickly maturing wheat and slowly maturing wheat. The same 36 growth state signature was used to identify both subcategories of wheat, but with two sets of growth state restrictions (see Table 5.5.4). This discrimination resulted in a total of 83% of the wheat being identified, with only 4% false classification.

5.5.2 Discussion of Second-Order Discrimination Results

In the second-order discrimination procedure, the user is faced with choices similar to those that must be made in the first-order procedure. The "unfilled" second-order signature is created from a growth state mapping generated during the creation of a first-order mean signature. The user therefore chooses the number of growth states and signature training sample for the second-order signature when creating a first-order mean signature. In the discrimination step, the user chooses which MSS Band/observation pairs to use, the amount of "fill" to use on the signature, and ranges of allowed growth states for each observation time. The larger the amount of "fill" the more pixels will be identified as in the crop class.

Second-order phenological discrimination has not been investigated to the same extent as first-order. The limited testing we have done does not indicate that second-order discrimination is an improvement over first-order.

5.5.3 Testing the Validity of Dynamic Programming in First-Order Mean Signature Generation

Recall that different observation times map into the same growth state in the construction of the first-order mean signature. In order to test whether it is good to allow observations from different times to be used in the construction of growth state, as is allowed in the GN1SIG mean first-order signature routine, an alternate procedure was implemented in program CH1SIG. Let us say we have G_0 as the number of growth states per observation time. In each iteration we define a mapping m: $(j,t) \rightarrow G$ which minimizes

$\sum_{t=1}^{T} \max_{i} |x(i,j,t) - u(m(j,t);i)|$ for each sample j, as in Section 5.1, with the additional restriction that the pair (j,t) must map into one of the growth states in the set $\{(t-1)G_0+1, (t-1)G_0+2, \ldots, G_0 t\}$. Because these sets are not overlapping, the method for finding the mapping turns out to be a simple manipulation.

A few phenological discrimination runs using five observation dates were made using mean signatures generated by CH1SIG, the first-order mean signature generation program which uses simple minimization. The results were not quite as good as with runs with GN1SIG, with dynamic programming. The average standard deviation by band and growth state for the samples mapped into 20 growth states by CH1SIG is 1.45 compared to an average of 1.42 when the samples are mapped by GN1SIG (see page 34). This demonstrates the validity of combining observations with different dates in characterizing a signature growth state.

5.5.4 An Experiment with Use of Two Signatures for Wheat

The identification of wheat has not been as good as hoped for, with the best results being about 80% correct identification and 5% false identification. First-order discrimination with a fairly small signature width results in about half the wheat being identified with a very small amount of false identification, when appropriate growth state restrictions are used. It was thought that perhaps wheat is better characterized by two or three signatures with small widths. Our experimentation did not lead to improved classification, but provides insight into the properties of the growth states in the signature.

A sequential procedure was used. Areas of wheat which were poorly identified by phenological discrimination were examined. It seemed that there were two types of wheat not being identified. One type was wheat with reflectances generally higher than average for all MSS Bands on all observations. The other type was wheat with generally lower than average

reflectances, especially for MSS Bands 4 and 5 on the May 9 observation. In order to try to identify these problem areas of "high" and "low" wheat, signatures were created from samples of wheat not yet identified. A "high" signature was created from pixels in this sample whose quantized values in MSS Bands 4 and 5 on the May 9 observation was below a threshold of 6. A "low" signature was created from pixels whose values in MSS Bands 4 and 5 on the May 9 observation was above 8. "High" and "low" wheat was classified with these signatures. The details of the procedure are outlined in Table 5.5.5 and the classified image is shown in Figure 21. Note that areas identified as "high" and "low" wheat are quite distinct.

The areas of "high" and "low" wheat were examined on the aerial photographs of Morton County. It was noted that small "low" wheat areas within fields were often near field borders, and are probably weedy areas. High areas within fields were often in areas that appeared to be high ground or light-colored, poor soil photographs.

We also investigated the "high" and "low" wheat by looking at field mean of Kauth greenness (KG) and Kauth soil brightness. Kauth soil brightness is a linear transformation of the MSS Bands, which we rescaled to fit in the 0-31 value range:

$$KSB = .522(.433\ MSS4 + .632\ MSS5 + .586\ MSS6 + .264\ MSS7)$$

Fields identified as primarily "high" wheat were areas of high KSB and about as much KG as field with predominantly "low" wheat, except on the May 9 date when they were "greener."

We investigated further by examining the samples for the "high" and "low" signature. We looked at a 36 growth stage signature created from a random sample of ground-truth wheat and found which growth states each observation of the sample mapped to (in the sense defined in Section 5.1). "Low" samples are mapped into relatively earlier growth states compared to the high reflectance samples, except for the October 23 observation.

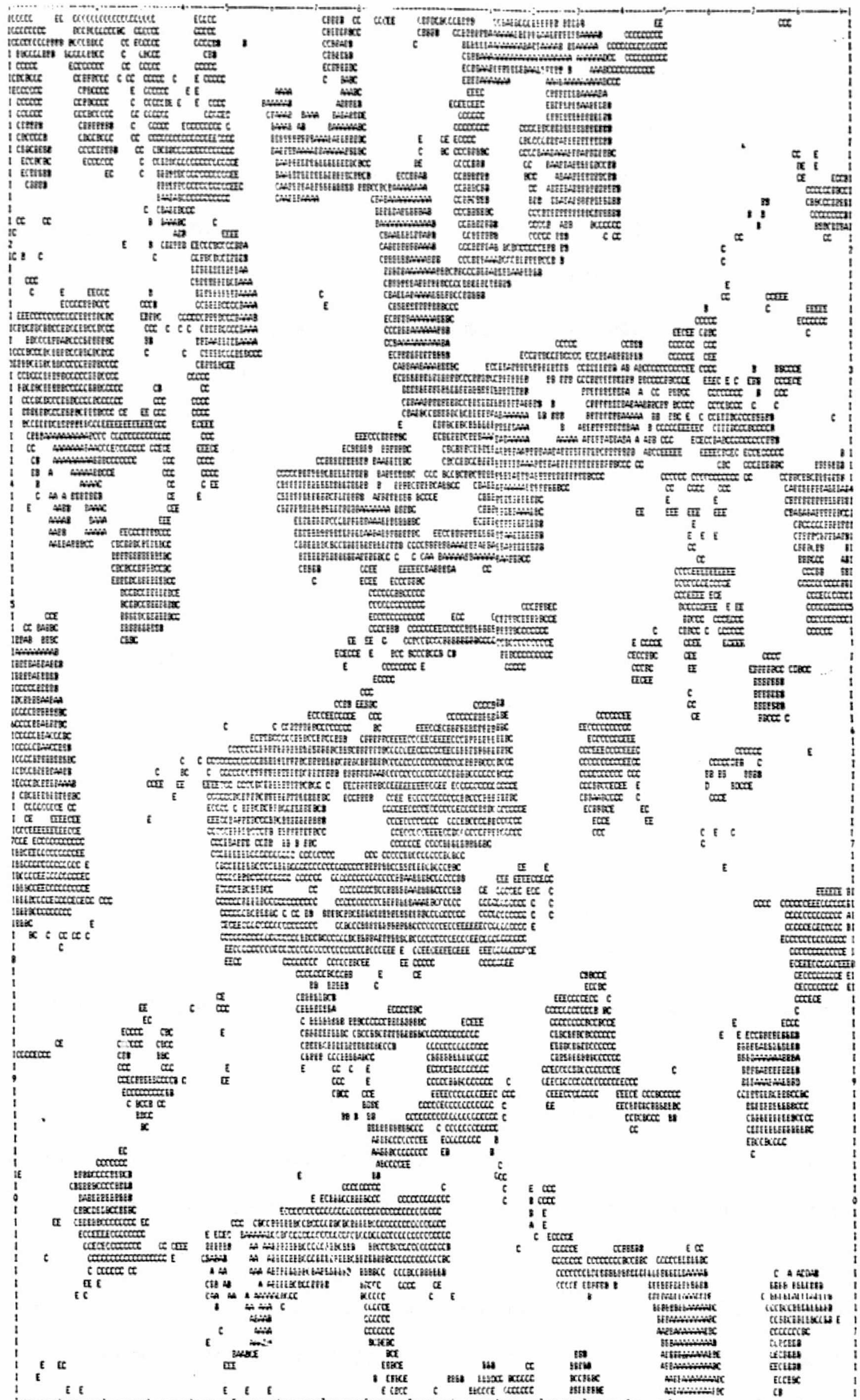
The explanation which seems most consistent in explaining the "high" and "low" areas is that "high" areas are poor quality stands of wheat, which are adversely effected by the dry weather in Morton County in 1974 or by poor soil. The "low" areas are vigorous stands of wheat, or areas with a lot of weeds. Vigorous stands of wheat mature more slowly than stands maturing in less than optimal conditions. The dryer fields will be the first to head, and therefore, look less green on May 9.

5.5.5 Summary and Review of Phenological Wheat in Morton County, Kansas

In our best phenological discrimination runs, we achieved about 80% correct identification of wheat with about 5% false identification, with 83% and 4% when all observation dates were used. This is about as good as wheat identification by the linear discrimination method, which resulted in 84% correct wheat identification and 4% false identification of wheat. Wheat identification was much better than with the Bayes table look-up method. In the case of these methods, however, multiple discrimination of several crops was carried out.

The phenological method identified the wheat fields much better than unsupervised clustering. This method had trouble identifying wheat fields that were clustered with summer fallow. As we have mentioned before in Section 4.3.1, we have suspected that some wheat fields were abandoned.

In the phenological discrimination process, each multi-spectral observation from a pixel at a single observation time is labeled as part of a cluster within crop type. The clustering method was designed so that each cluster would contain observations at the same degree of maturity. Our experimental results are consistent with the interpretations of the clusters, but not conclusive. There is significant correlation between factors such as irrigation and growth rate. In order to find out what factors the clusters are associated with and in order to refine the clustering process, we need



KEY:

Symbol-	A	B	C	D	E
Growth state-	1	2	3	4	5

Figure 16. Image of growth state identifications made on the Oct. 23 observation of the Morton County ITS. Growth state restrictions (1-5)

Figure 17. Image of growth state identifications made on the May 9 observation of the Morton County ITS. Growth state restrictions (10-12)

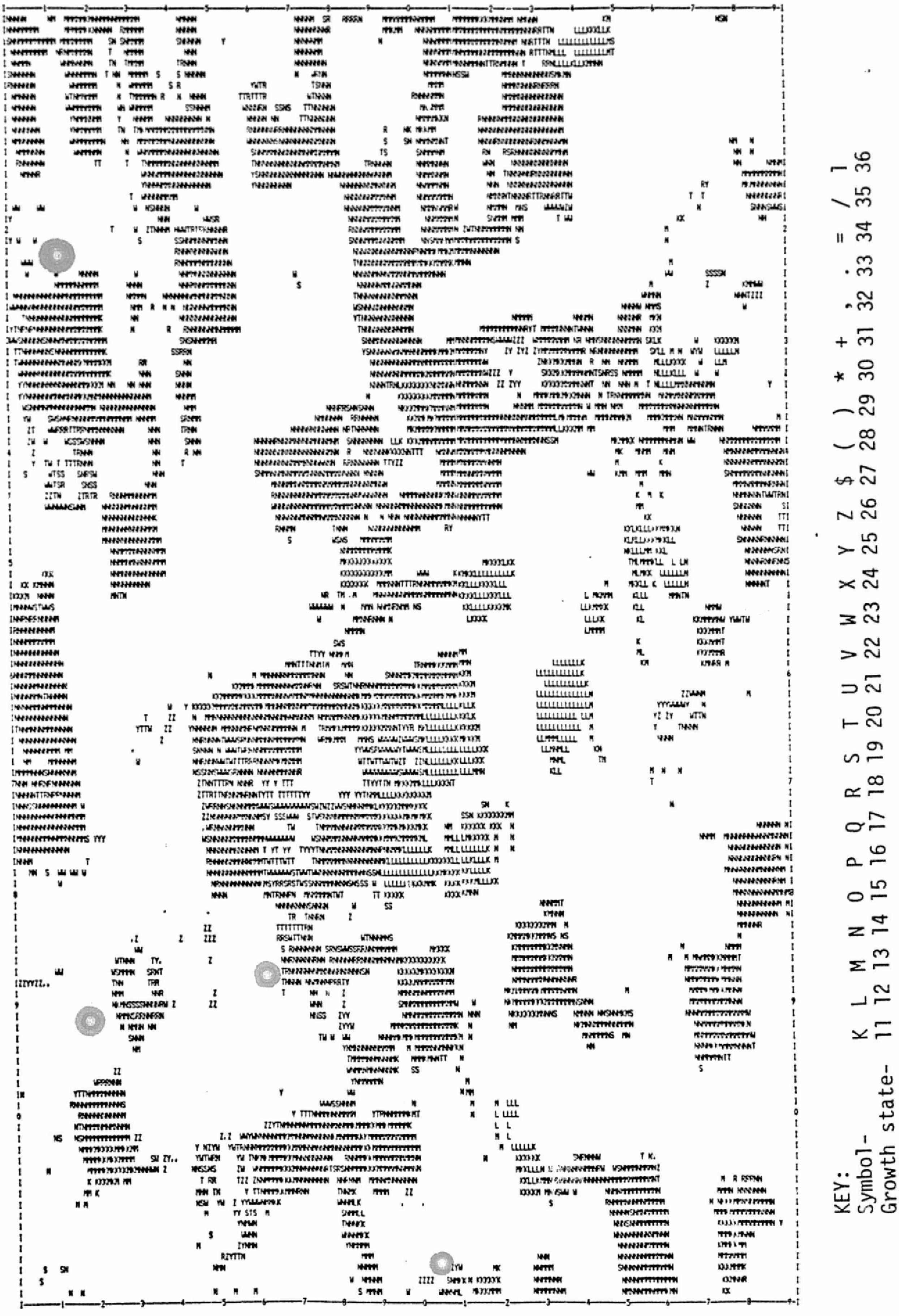
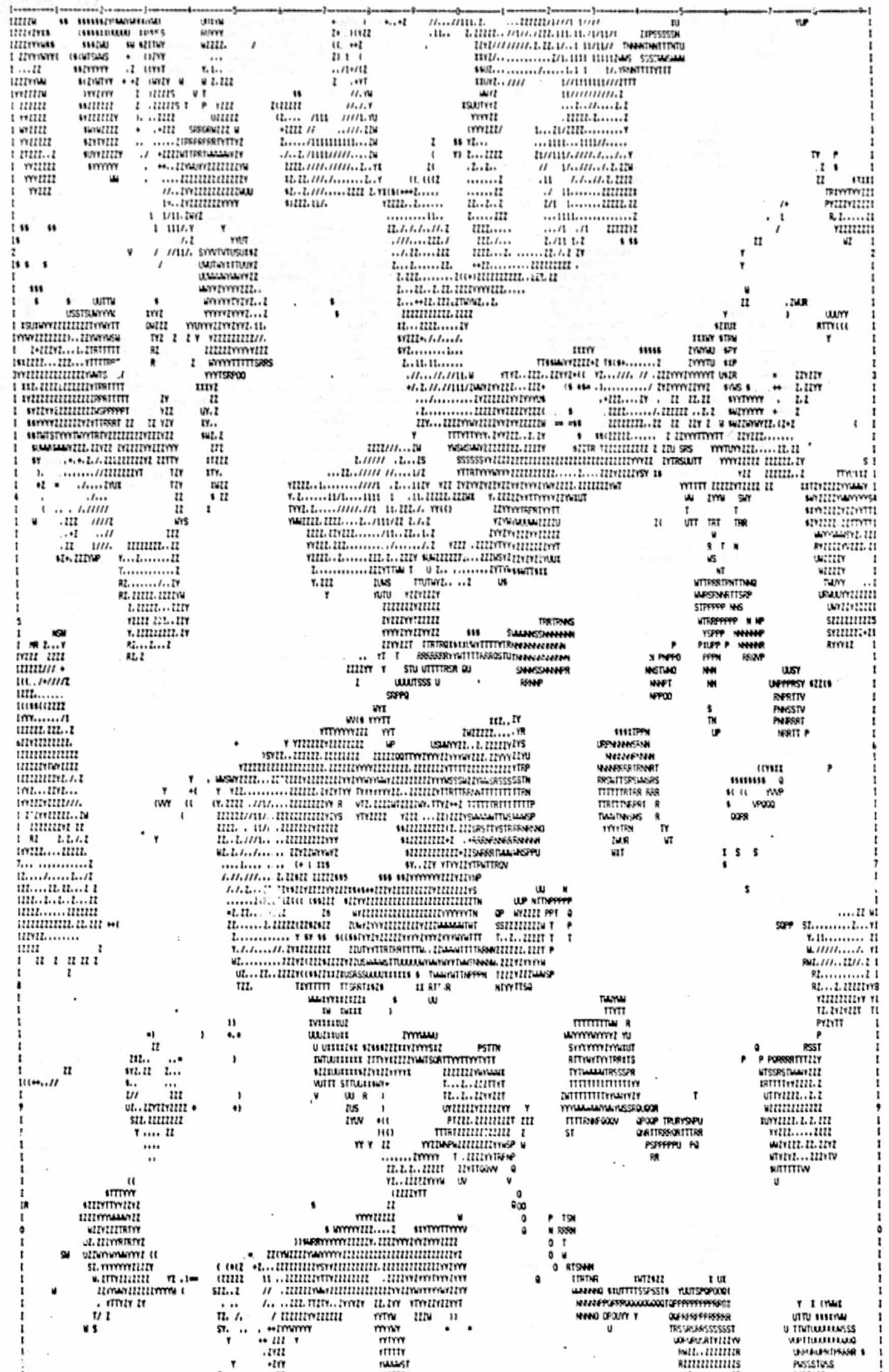


Figure 18. Image of growth state identifications made on the May 27 observation of the Morton County ITS. Growth state restrictions (1-36)

KEY:

Symbol-	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	$	(	)	*	+	,	.	=	/	1
Growth state-	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36

Figure 19. Image of growth state identifications made on the June 14 observation of the Morton County ITS. Growth state restrictions (1-36)



KEY:
Symbol- K L M N O P Q R S T U V W X Y Z $ ( ) * + , . = / 1
Growth state- 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36

Figure 20. Image of growth state identifications made on the July 2 observation of the Morton County ITS. Growth state restrictions (1-36)

to test the procedure on ground truth with detailed information of crop condition and maturity.

The growth state identifications made in the discrimination process are the earliest growth states consistent with the multi-spectral observations, allowed growth states for observation date, and the requirement that growth states be chronologically ordered. In order to use the growth state identification for information on crop maturity, it might be better to identify "best" consistent rather than earliest consistent growth states. Our identification may also be improved if our signature width varies with band and growth state. We plan extensive testing of second-order phenological discrimination and use of first-order phenological signatures with varying width.

Figure 21. Identification of Morton County wheat with two signatures:

A = identified as wheat with "high" signature
B = identified as wheat with "low" signature
C = identified as wheat with both signatures

TABLE 5.5.1

SAMPLE ADEQUACY: COMPARISON OF CLASSIFICATION RESULTS
WITH FIRST-ORDER DISCRIMINATION AND NO USER SPECIFIED GROWTH STATE RESTRICTIONS

WHEAT SAMPLE DESCRIPTION	NUMBER OF GROWTH STATES	MSS BANDS USED	SIGNATURE WIDTH	% CORRECT IDENTIFICATION OF WHEAT	% FALSE IDENTIFICATION
120 pixels	20	4,5,6	2.0	59%	2%
35 wheat field averages	20	4,5,6	2.0	53%	4%
232 pixels	20	4,5,6	2.0	62%	4%
130 pixels	20	4,5,6	2.0	63%	6%
103 pixels	20	4,5,6	2.0	54%	6%

CONTINGENCY TABLE FOR MORTBGCGT - 22 M36SP9DB6 - 1 SCALE FACTOR 10** 0

36 Growth State Signature
MSS Bands Used - 4,5,6
Tolerance Width - 2.0
Growth State Restrictions:
May 9 (10-12)

COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GRASS	CORN	SUFAL	GSORG	RYE	TOTAL	#ERR	% ERR	% SD
UNKWN	8485	4320	0	0	0	0	0	12805	0	0	0
WHEAT	1167	2818	0	0	0	0	0	3985	0	0	0
GRASS	742	286	0	0	0	0	0	1028	286	100	1
CORN	704	36	0	0	0	0	0	740	36	100	0
SUFAL	3087	40	0	0	0	0	0	3127	40	100	0
GSORG	209	11	0	0	0	0	0	220	11	100	1
RYE	217	34	0	0	0	0	0	251	34	100	2
TOTAL	14611	7545	0	0	0	0	0	22156	407	83	0
#ERR	0	407	0	0	0	0	0	407	****	*****	****
% ERR	0	13	0	0	0	0	0	2	****	*****	****

Table 5.5.2. Phenological discrimination of Morton County wheat using only one observation date.

CONTINGENCY TABLE FOR MORTBGCGT - 22 M36SP9DC8 - 1 SCALE FACTOR 10** 0

36 Growth State Signature
MSS Bands Used - 4,5,6
Tolerance Width - 3.25
Growth State Restrictions:
October 23 (1-5)
May 9 (10-12)

COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GRASS	CORN	SUFAL	GSORG	RYE	TOTAL	#ERR	% ERR	% SD
UNKWN	8211	4594	0	0	0	0	0	12805	0	0	0
WHEAT	774	3211	0	0	0	0	0	3985	0	0	0
GRASS	1008	20	0	0	0	0	0	1028	20	100	0
CORN	680	60	0	0	0	0	0	740	60	100	1
SUFAL	2992	135	0	0	0	0	0	3127	135	100	0
GSORG	189	31	0	0	0	0	0	220	31	100	2
RYE	211	40	0	0	0	0	0	251	40	100	2
TOTAL	14065	8091	0	0	0	0	0	22156	286	83	0
#ERR	0	286	0	0	0	0	0	286	****	*****	****
% ERR	0	8	0	0	0	0	0	1	****	*****	****

Table 5.5.3. Phenological discrimination of Morton County wheat using two observation dates.

CONTINGENCY TABLE FOR MORTGGCGT - 22 M36CP2DA4 - 1 SCALE FACTOR 10** 0

36 Growth State Signature
MSS Bands Used - 4,5,6
Tolerance Width - 3.50
Growth State Restrictions

Slow Wheat:

October 23 (2-6)
May 9 (10-12)
May 23 (15-19)

Fast Maturing Wheat:

1-2
14-18
24-27

COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GRASS	CORN	SUFAL	GSORG	RYE	TOTAL	#ERR	% ERR	% SD
UNKWN	8049	4756	0	0	0	0	0	12805	0	0	0
WHEAT	687	3298	0	0	0	0	0	3985	0	0	0
GRASS	998	30	0	0	0	0	0	1028	30	100	0
CORN	718	22	0	0	0	0	0	740	22	100	0
SUFAL	3004	123	0	0	0	0	0	3127	123	100	0
GSORG	205	15	0	0	0	0	0	220	15	100	1
RYE	211	40	0	0	0	0	0	251	40	100	2
TOTAL	13872	8284	0	0	0	0	0	22156	230	83	0
#ERR	0	230	0	0	0	0	0	230	****	*****	****
% ERR	0	7	0	0	0	0	0	1	****	*****	****

Table 5.5.4. Phenological discrimination of Morton County wheat using three observation dates.

CONTINGENCY TABLE FOR MORTBGCGT - 22 MC1230DIS - 1 SCALE FACTOR 10** 0

10 Growth State Signatures
MSS Bands Used - 4,5,6
Tolerance Width - 4.0
Growth State Restrictions
October 23 (1,2)
May 9 (2,4)
May 27 (4,6)
June 14 (6,8)
July 2 (8,10) for one signature only

COL = ASSIGN CAT
ROW = TRUE CAT

	R DEC	WHEAT	GRASS	CORN	SUFAL	GSORG	RYE	TOTAL	#ERR	% ERR	% SD
UNKWN	7106	5699	0	0	0	0		12805	0	0	0
WHEAT	365	3620	0	0	0	0	0	3985	0	0	0
GRASS	903	125	0	0	0	0	0	1028	125	100	1
CORN	721	19	0	0	0	0	0	740	19	100	0
SUFAL	2823	304	0	0	0	0	0	3127	304	100	0
GSORG	211	9	0	0	0	0	0	220	9	100	1
RYE	206	45	0	0	0	0	0	251	45	100	2
TOTAL	12335	9821	0	0	0	0	0	22156	502	82	0
#ERR	0	502	0	0	0	0	0	502	****	*****	****
% ERR	0	12	0	0	0	0	0	2	****	*****	****

Table 5.5.5. Phenological discrimination of Morton County wheat using three signatures to characterize wheat.

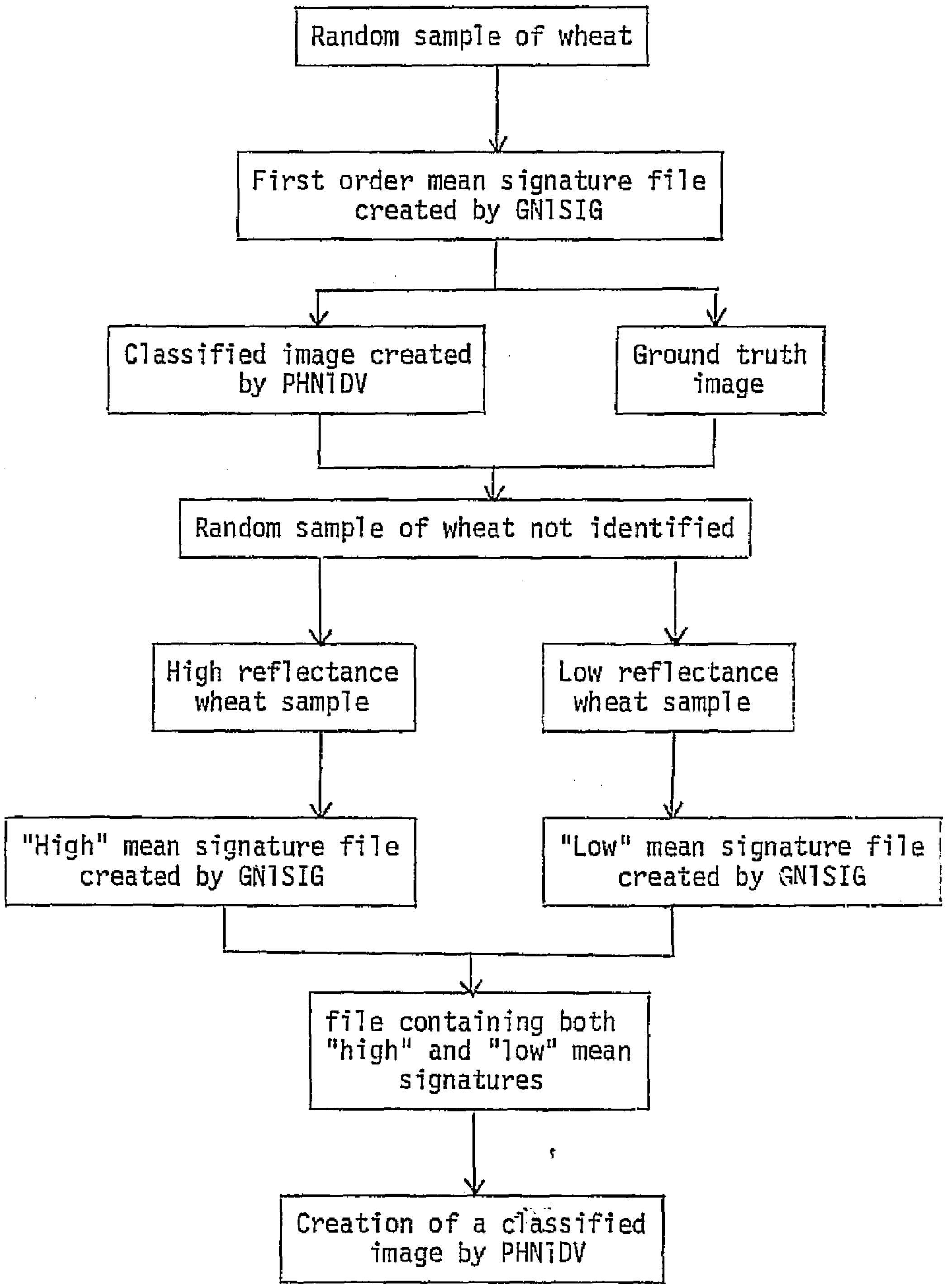


Table 5.5.6. An experiment in identifying wheat with two signatures.

AVERAGES AND STANDARD DEVIATIONS

GROWTH STATE 1 WITH 8 SAMPLES			
23.12	24.25	12.25	21.12
0.93	0.97	0.43	1.54
GROWTH STATE 2 WITH 24 SAMPLES			
19.17	21.87	11.54	20.50
1.07	1.05	0.58	1.41
GROWTH STATE 3 WITH 13 SAMPLES			
15.15	18.15	11.69	22.92
1.17	1.23	0.61	1.38
GROWTH STATE 4 WITH 20 SAMPLES			
17.00	19.95	10.70	18.15
0.89	1.16	0.46	0.85
GROWTH STATE 5 WITH 13 SAMPLES			
14.00	17.54	11.08	20.23
1.41	1.34	0.62	1.37
GROWTH STATE 6 WITH 15 SAMPLES			
15.20	18.87	10.07	14.40
1.60	0.96	0.85	1.50
GROWTH STATE 7 WITH 3 SAMPLES			
9.67	13.67	9.67	17.00
0.94	0.94	0.47	1.41
GROWTH STATE 8 WITH 6 SAMPLES			
11.50	16.33	8.33	9.33
0.76	0.75	0.47	0.47
GROWTH STATE 9 WITH 4 SAMPLES			
9.50	15.00	7.50	6.75
0.87	1.00	0.50	0.43
GROWTH STATE 10 WITH 53 SAMPLES			
6.68	7.21	9.26	12.13
0.84	0.85	0.85	0.70
GROWTH STATE 11 WITH 25 SAMPLES			
3.76	3.88	7.88	12.64
1.34	1.53	1.42	1.13
GROWTH STATE 12 WITH 7 SAMPLES			
2.29	1.86	13.29	14.00
1.16	1.25	0.45	1.07
GROWTH STATE 13 WITH 8 SAMPLES			
6.00	6.25	11.37	15.37
1.41	1.20	1.22	0.86
GROWTH STATE 14 WITH 23 SAMPLES			
8.26	9.87	10.91	13.09
0.94	0.80	0.78	0.83
GROWTH STATE 15 WITH 10 SAMPLES			
5.60	5.90	15.50	15.90
1.02	1.04	0.67	1.22
GROWTH STATE 16 WITH 28 SAMPLES			
8.18	9.50	15.71	15.07
1.00	1.05	0.92	0.84
GROWTH STATE 17 WITH 7 SAMPLES			
7.29	8.57	12.86	12.00
0.88	1.18	0.64	1.07
GROWTH STATE 18 WITH 24 SAMPLES			
8.96	10.42	17.21	15.79
1.02	0.95	0.96	0.96
GROWTH STATE 19 WITH 16 SAMPLES			
9.31	10.75	16.81	17.94
0.92	1.03	1.13	0.83
GROWTH STATE 20 WITH 22 SAMPLES			
11.18	12.50	17.95	17.55
0.89	1.03	0.98	1.08
GROWTH STATE 21 WITH 7 SAMPLES			
9.71	12.00	7.43	8.14
1.16	1.07	0.73	0.64
GROWTH STATE 22 WITH 11 SAMPLES			
9.82	10.91	14.09	16.55
0.72	1.08	0.51	0.66
GROWTH STATE 23 WITH 8 SAMPLES			
12.00	14.37	9.87	10.25
0.71	0.86	1.62	1.64
GROWTH STATE 24 WITH 11 SAMPLES			
10.73	12.36	15.09	17.45
0.62	0.64	0.79	0.99
GROWTH STATE 25 WITH 15 SAMPLES			
12.33	13.87	15.87	16.87
1.19	0.72	1.26	1.02
GROWTH STATE 26 WITH 15 SAMPLES			
15.47	16.20	14.93	15.53
1.26	1.28	1.24	1.71
GROWTH STATE 27 WITH 10 SAMPLES			
11.90	13.90	16.20	19.80
0.94	1.04	0.60	0.60
GROWTH STATE 28 WITH 13 SAMPLES			
13.31	14.31	15.92	17.08
1.54	1.68	1.59	1.64
GROWTH STATE 29 WITH 22 SAMPLES			
14.32	15.27	17.50	19.50
0.82	0.91	1.08	0.99
GROWTH STATE 30 WITH 6 SAMPLES			
14.50	15.17	21.83	20.50
1.71	0.69	1.07	0.96
GROWTH STATE 31 WITH 13 SAMPLES			
15.46	16.15	19.69	21.08
1.22	0.77	0.61	1.07
GROWTH STATE 32 WITH 7 SAMPLES			
18.43	17.71	18.29	21.00
0.73	0.88	0.88	1.41
GROWTH STATE 33 WITH 9 SAMPLES			
17.22	18.00	20.33	21.44
0.79	0.82	0.47	0.68
GROWTH STATE 34 WITH 9 SAMPLES			
18.00	17.44	23.11	23.33
1.25	0.96	1.29	1.49
GROWTH STATE 35 WITH 16 SAMPLES			
19.94	19.37	21.06	21.69
1.20	0.93	1.14	1.21
GROWTH STATE 36 WITH 29 SAMPLES			
21.72	20.69	23.90	24.03
1.11	1.18	1.18	1.92

Table 5.5.7. The averages (which constitute mean signature) and standard deviation by growth state and MSS band of subsamples of a 106 wheat pixel sample of the Morton County Intensive Test Site.

ORIGINAL PAGE IS OF POOR QUALITY

6.0 GROUND TRUTH EVALUATION FOR MORTON COUNTY

After our experimentation with the Morton County data, we found out that the U.S. Department of Agriculture/Agricultural Stabilization and Conservation Service takes field surveys in the LACIE Intensive Test Sites. The Morton County ASCS Office sent us a copy of the 1974 Land Use Inventory for the Morton County LACIE Intensive Study Site, along with a copy of the 1973-1974 Ground Truth Data Package which provided instructions for its completion.

We have been able to confirm some of our ideas about the ground truth fields. About 20% of the ground truth wheat acreage on the Morton ITS was abandoned due to drought or destroyed by insects (see Appendix H). These fields correlated highly with areas that were poorly identified by our phenological classifier. Some of these fields were also clustered with summer fallow in our unsupervised clustering images. Fertilized and irrigated fields constitute about 24% of the wheat acreage on the Morton County ITS. These fields correlate very well with areas we identified with as "low" signature in Section 5.4.1.4.

7.0 RECOMMENDATIONS

The phenological method seems to be about as good for crop discrimination as more traditional methods of crop classification. Our testing has been limited to two sites; more extensive studies need to be done in order to evaluate phenological classification adequately. Also, the method needs to be refined to improve its ability to show the degree of maturity of the crop on the observation dates. In particular:

(1) Phenological discrimination needs to be tested on sites for which detailed ground truth is available. Surveys of crop condition and growth state can be used to evaluate the phenological growth stage identifications.

(2) The signature can be refined. One possibility is to construct first-order signatures, allowing the signature width to vary with band and growth state.

(3) The identification rule used in the process of phenological discrimination can be modified so that the "best" growth state identification is made, rather than first possible.

REFERENCES

1. Bernstein, R., "Digital Image Processing--Past, Present, and Future," Proceedings of the International Symposium on Image Processing, Interactions with Photogrammetry and Remote Sensing, Graz, October 3-5, 1977.

2. Kaneko, T., "Crop Classification Using Time Features Computed from Multi-Temporal Multi-Spectral Data," 1978 Pattern Recognition Conference, Japan, 1978.

3. Engvall, J.L., J.D. Tubbs, and Q.A. Holmes, "Pattern Recognition of LANDSAT Data Based Upon Temporal Trend Analysis," Remote Sensing of Environment 6, 1977, pp. 303-314.

4. Misra, P.N. and S.G. Wheeler, "Crop Classification with LANDSAT Multi-spectral Scanner Data," Pattern Recognition 10, 1978, pp. 1-13.

5. Megier, J., "Multi-Temporal Digital Analysis of LANDSAT Data for Inventory of Poplar Planted Groves in North Italy," Proceedings of the International Symposium on Image Processing, Interactions with Photogrammetry and Remote Sensing, Graz, October 3-5, 1977.

6. Carlson, R.E. and C. Aspiazu, "Cropland Acreage Estimates from Temporal, Multi-Spectral ERTS-1 Data," Remote Sensing of Environment 4, 1975, pp. 237-243.

7. Kanemasu, E.T., "Seasonal Canopy Reflectance Patterns of Wheat, Sorghum, and Soybeans," Remote Sensing of Environment 3, 1974, pp. 43-47.

8. Landgrebe, D., "Computer-Based Remote Sensing Technology--A Look to the Future," Remote Sensing of Environment 5, 1976, pp. 229-246.

9. Vinogradov, V., "Remote Sensing in Ecological Botany," Remote Sensing of Environment 6, 1977, pp. 83-94.

10. Morain, E.G., "Kansas Environmental and Resource Study: A Great Plains Model--Extraction of Agricultural Statistics from ERTS-1 Data of Kansas," Final Report, University of Kansas Center for Research, Inc., NASA Contract NAS5-21822, Task 4, 1974.

11. Kalensky, Z. and L.R. Scherk, "Accuracy of Forest Mapping from LANDSAT Computer Compatible Tapes," Tenth International Symposium on Remote Sensing of Environment, Ann Arbor, Michigan, October 6-10, 1975.

12. Swain, P.H., "Land Use Classification and Mapping by Machine-Assisted Analysis of LANDSAT Multi-Spectral Scanner Data," Final Report, Purdue University, LARS, USGS Contract 14-08-0001-14725, 1976.

C - 2

13. Von Steen, D.A. and W.H. Wigton, "Crop Identification and Acreage Measurement Utilizing LANDSAT Imagery," Statistical Reporting Service--U.S. Department of Agriculture, March 1976.

14. Landgrebe, D.A., et. al., "A Studv of the Utilization of ERTS-1 Data from the Wabash River Basin," Final Report, Purdue University, LARS, NASA Contract NAS 5-21773, 1974.

15. Nalepka, R.F., J.E. Colwell, and D.P. Rice, "Forecasts of Winter Wheat Yield and Production Using LANDSAT Data," Final Report, University of Michigan, ERIM, NASA Contract NAS5-22398, December 1977.

16. Erickson, L.D. and R.F. Nalepka, "PROGRAMS: A Second Generation Multi-Spectral, Multi-Temporal Processing System for Agricultural Mensuration," Purdue University, Purdue: LARS Symposium Proceedings on Machine Processing of Remotely Sensed Data, IEEE Catalog No. 76CH1103-1 MPRSD, 1976.

17. Kauth, R.J. and G.S. Thomas, "The Tasselled Cap--A Graphic Description of the Spectral-Temporal Development of Agricultural Crops as Seen by LANDSAT," Purdue: LARS Symposium Proceedings on Machine Processing of Remotely Sensed Data, IEEE Catalog No. 76CH1103-1 MPRSD, 1976.

18. Kauth, R.J., A.P. Pentand, and G.S. Thomas, "BLOB: An Unsupervised Clustering Approach to Spatial Preprocessing of MSS Imagery," Eleventh International Symposium on Remote Sensing of Environment, University of Michigan, ERIM, 1977.

19. Carlson, Maestede, Fenton, Thomson, and Epstein, "Remote Sensing in Iowa Agricuture: Identification and Classification of Iowa's Crops, Soils, and Forestry Resources Using ERTS-1 and Complimentary Underflight Imagery," Final Report, Iowa State University, NASA Contract NAS5-21839, 1974.

20. Salmon and Drexler, "Reducing LANDSAT Data to Parameters with Physical Significance," Proceedings of the Eleventh International Symposium on Remote Sensing of Environment, University of Michigan, ERIM, 1977.

21. Gammon, P.T., D. Malone, P.D. Brooke, and V. Carter, "Three Approaches to the Classification and Mapping of Inland Wetlands," Proceedings of the Eleventh Symposium on Remote Sensing of Environment, University of Michigan, ERIM, 1977.

22. Gammon, P.T. and V.P. Carter, "Comparison of Vegetation Classes in the Great Dismal Swamp Using Two Individual LANDSAT Images and a Temporal Composite," Purdue: LARS Symposium on Machine Processing of Remotely Sensed Data, IEEE Catalog No. CH1103-IMPRSD, 1976.

23. Flores, L.M. and D.T. Register, "Evaluation of Classification Procedures for Estimating Wheat Acreage in Kansas," Purdue: LARS Symposium Proceedings on Machine Processing of Remotely Sensed Data, IEEE Catalog No. 76CH1103-1 MPRSD, 1976.

24. Le Toan, T.Y., C. Cassirame, and J. Quash, "Inventory of Rice Fields in France Using LANDSAT and Aircraft Data," Proceedings of the Eleventh Symposium on Remote Sensing of Environment, University of Michigan, ERIM, 1977.

25. Bauer, M.E., "The Role of Remote Sensing in Determining Distribution and Yield of Crops," Advances in Agronomy 27, 1975, pp. 271-304.

26. Haralick, R.M., "The Table Look-Up Rule," Communication Statis. Theor. Math A5, Vol. 12, 1976, pp. 1163-1191.

27. Haralick, R.M. and W.F. Bryant, "Documentation of Procedures for Textural/Spacial Pattern Recognition," Final Report, University of Kansas Center for Research, Inc., RSL Technical Report 278-1, April 15, 1976.

28. Bryant, W., R.M. Haralick, D. Johnson, G. Minden, C. Paul, and A. Singh, "KANDIDATS II--Kansas Digital Image Data System," University of Kansas Center for Research, Inc., RSL Technical Report 0920-2, September 1976.

29. Haralick, R.M. and J. Kartus, "Arrangements and Homomorphisms," to be published in IEEE Systems, Man, and Cybernetics, August 1978.

30. Dixon, W.J., BMDP--Biomedical Computer Programs, University of California, Berkeley Press, 1975.

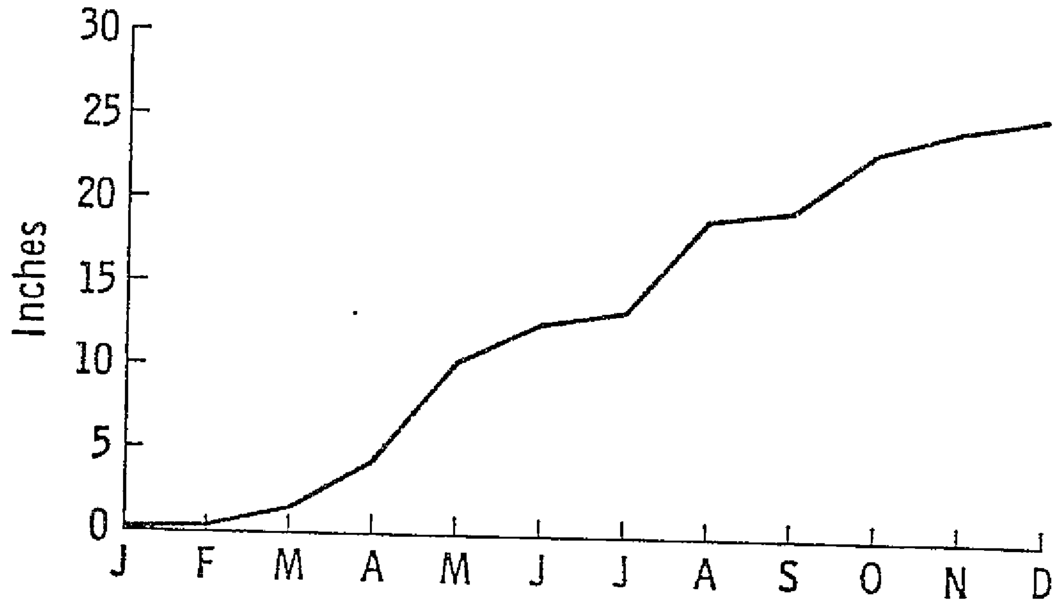
31. Neely, P., "REGRESS--Stepwise Multiple Linear Regression Program" and "PRINCOMP--Principal Components Program," University of Kansas, Academic Computing Center, 1971-1974.

32. Toussaint, T., "On the Divergence Between Two Distributions and the Probability of Misclassification of Several Rules," Proceedings of the Second International Joint Conference on Pattern Recognition, Copenhagen, Denmark, August 1974.

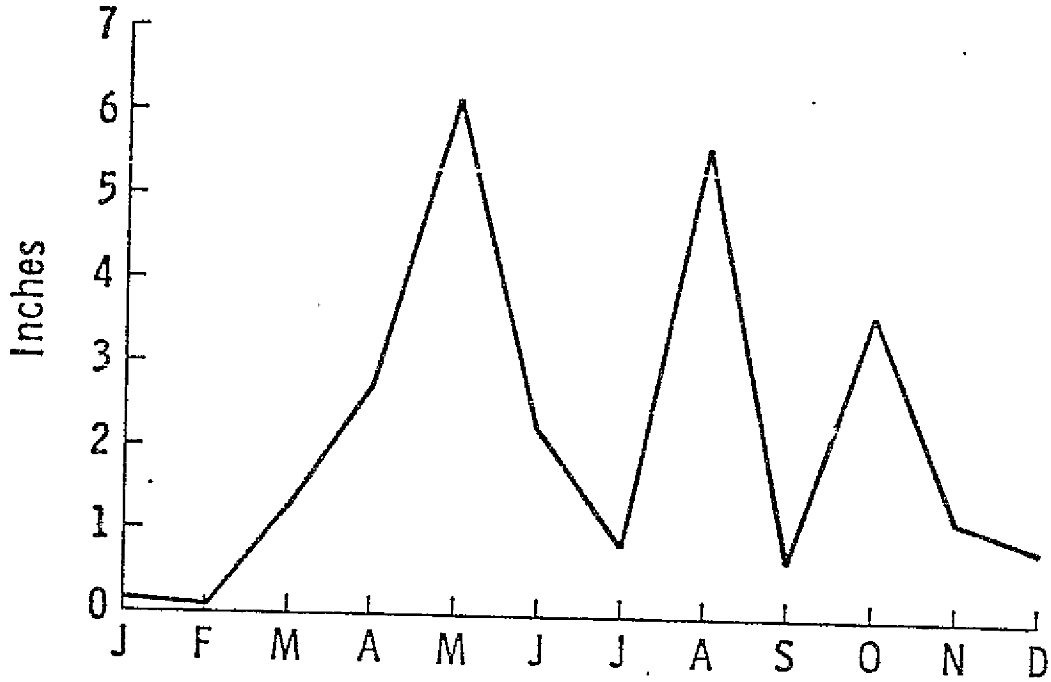
33. Ball, G.H. and D.J. Hall, "ISODATA, A Novel Method of Data Ahalysis and Pattern Classification," Stanford Research Institute, Menlo Park, California, April 1975.

APPENDIX A

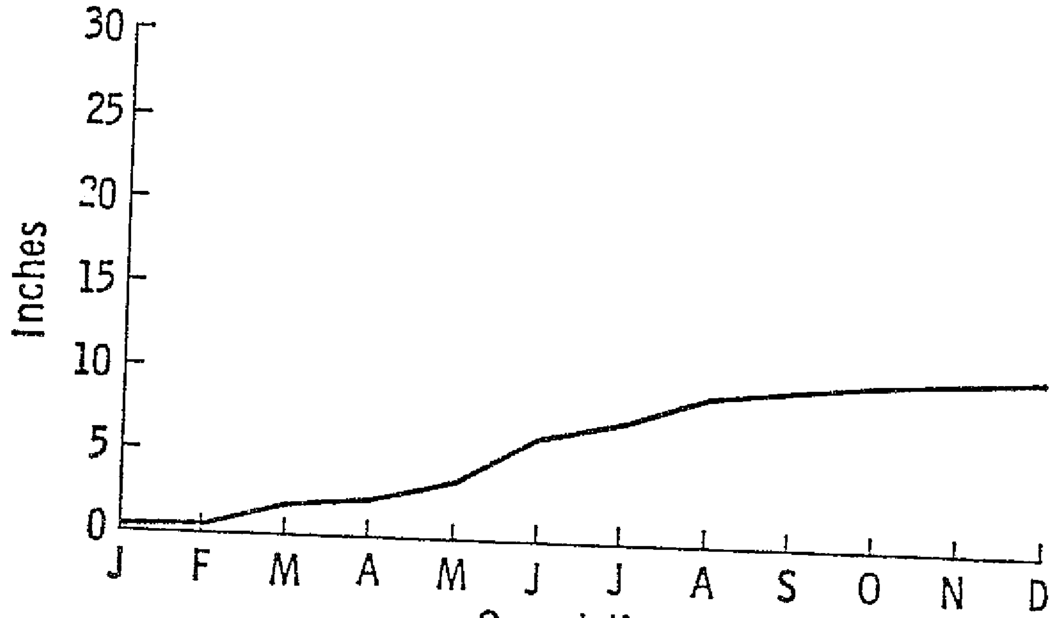
Precipitation and temperature graphs for 1974 for the five test sites.



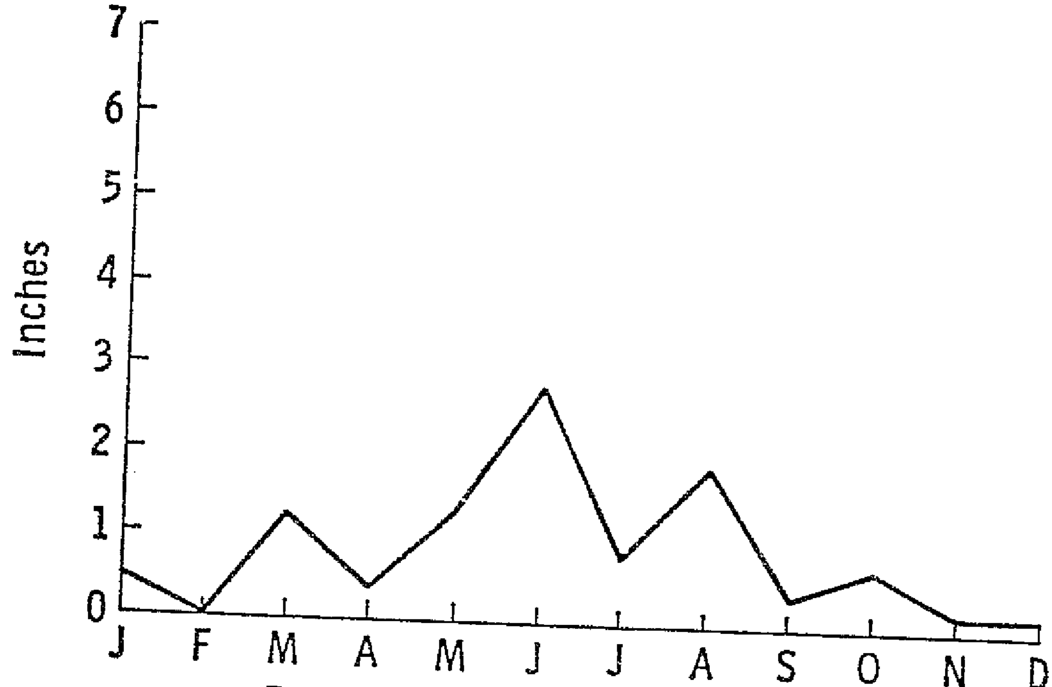
Cumulative



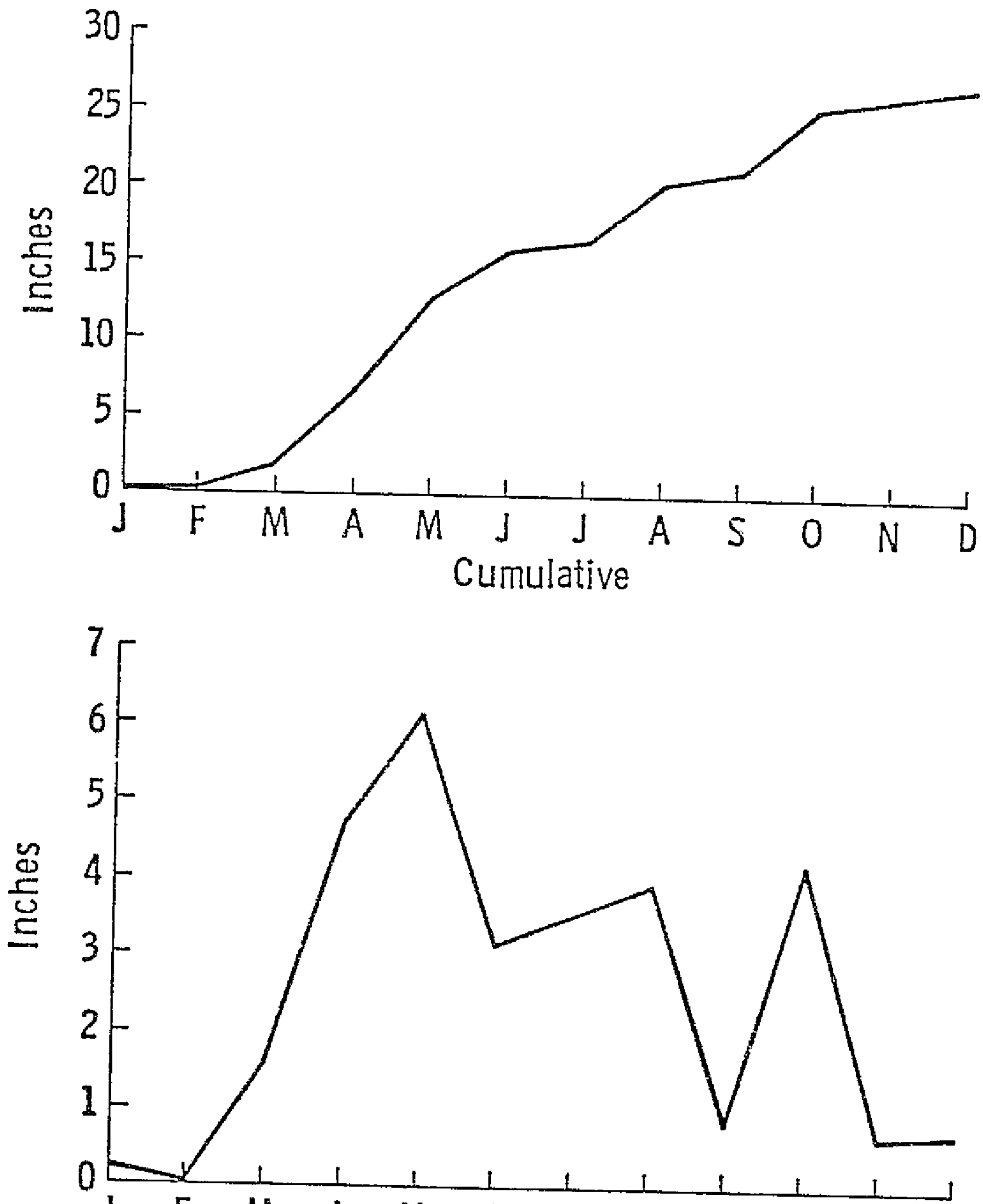
Precipitation, 1974, Rice County



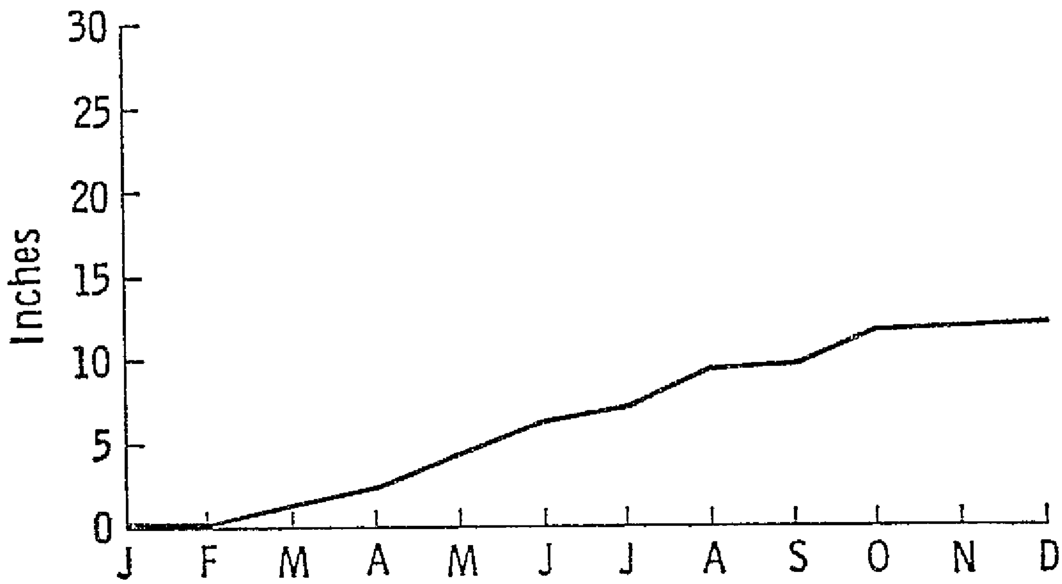
Cumulative



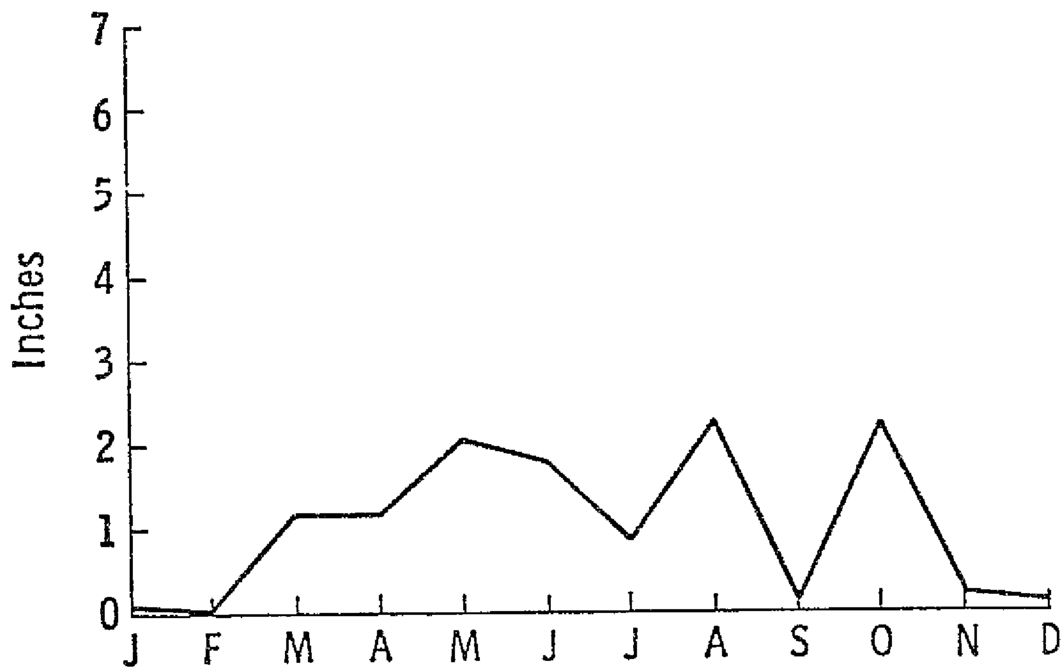
Precipitation, 1974, Morton County



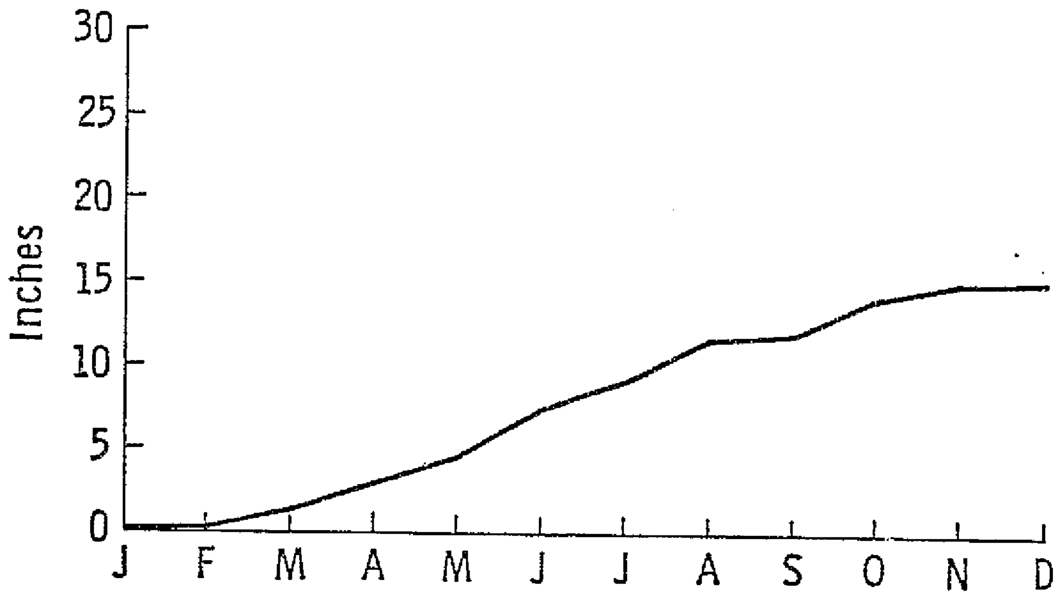
Precipitation, 1974, Saline County



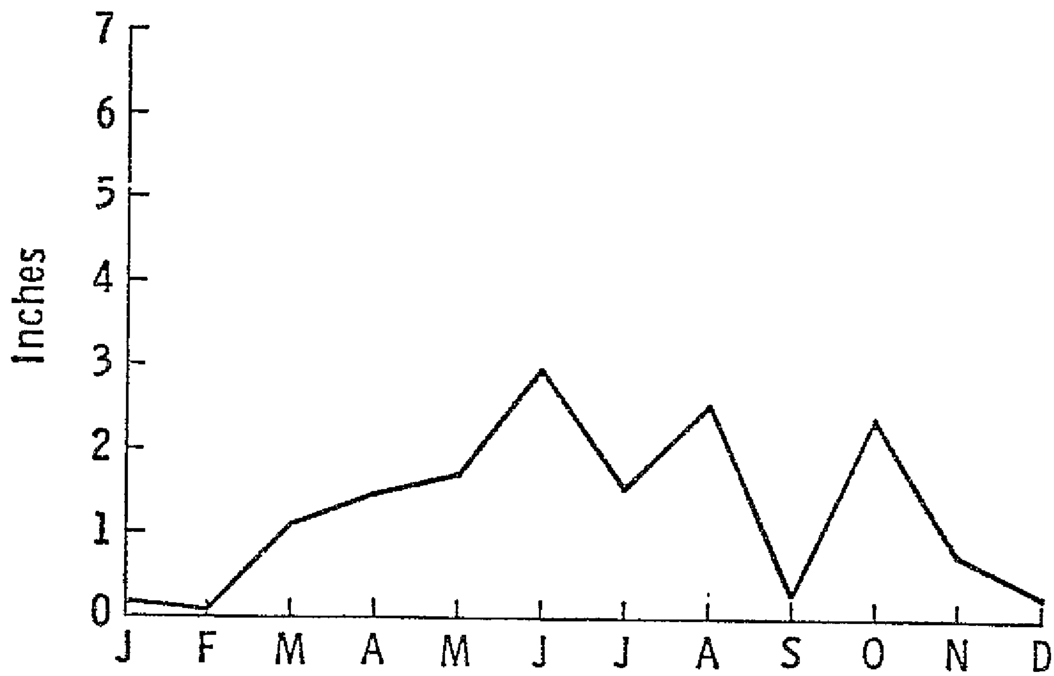
Cumulative



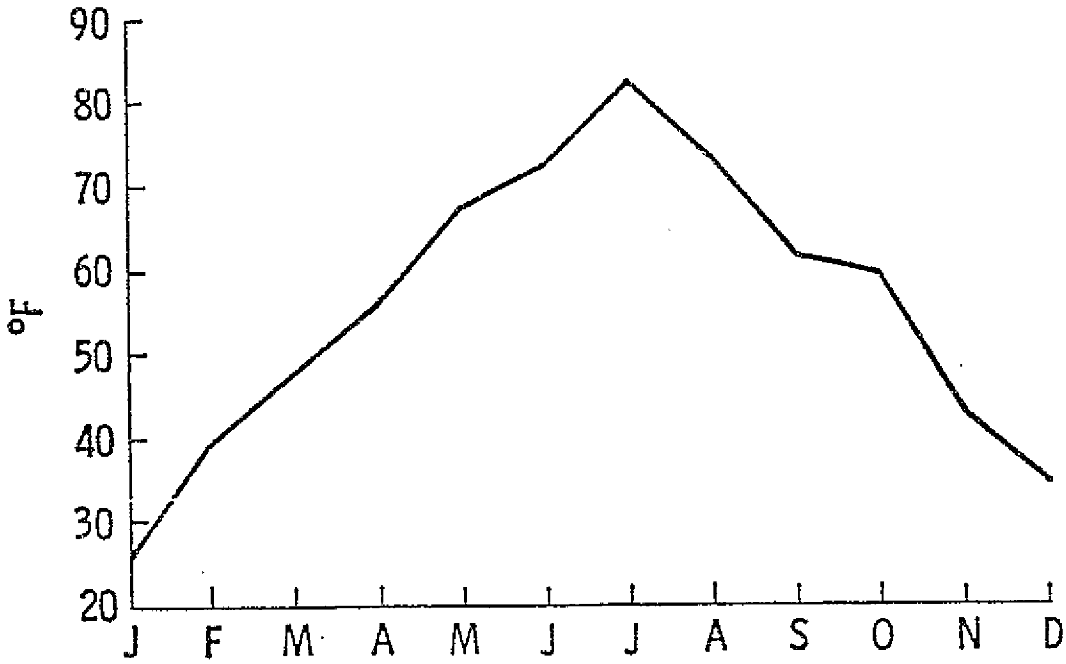
Precipitation, 1974, Finney County



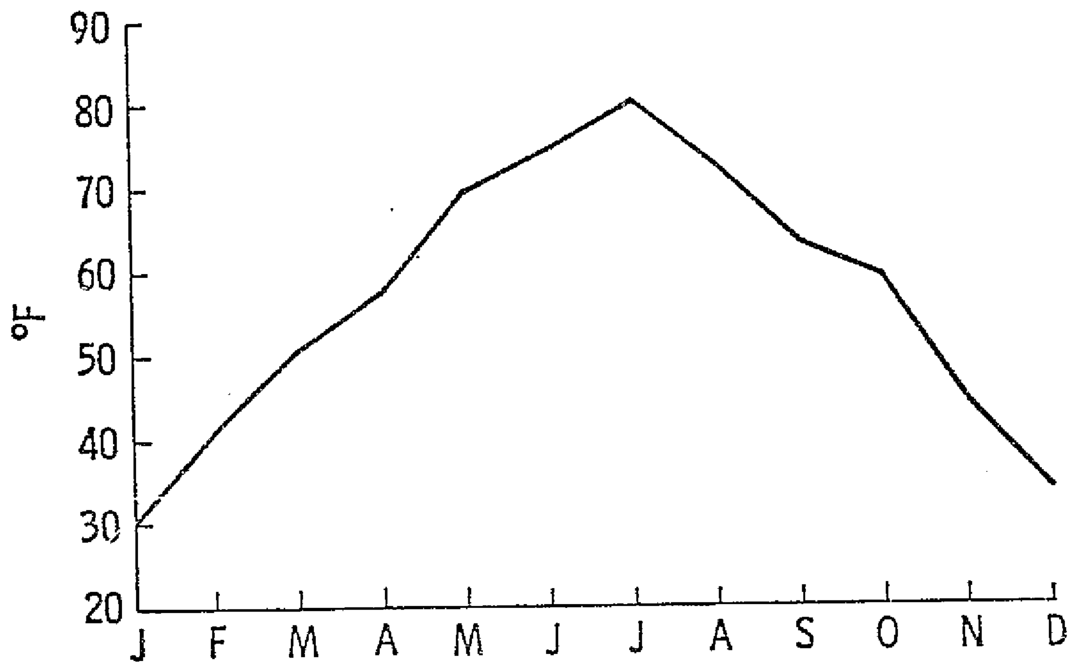
Cumulative



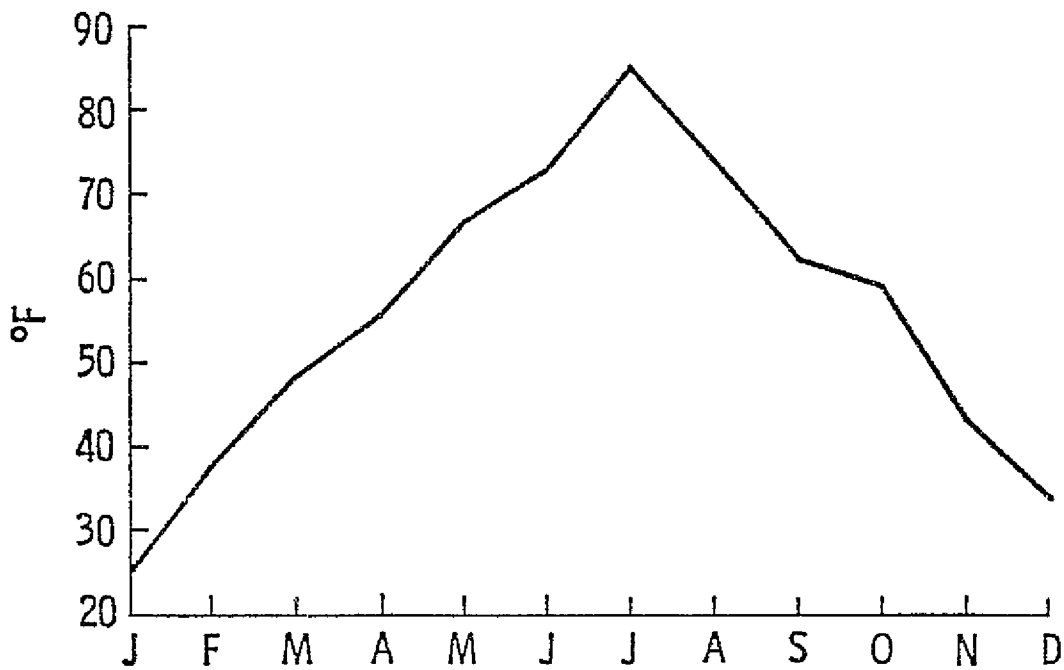
Precipitation, 1974, Ellis County



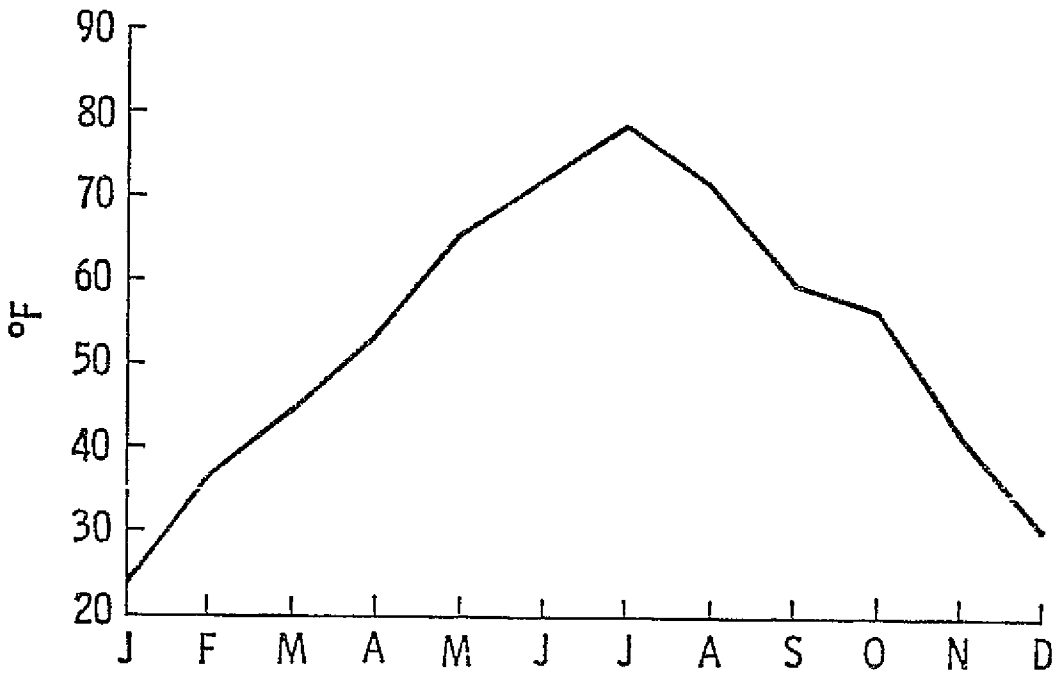
Average Temperatures, 1974, Rice County



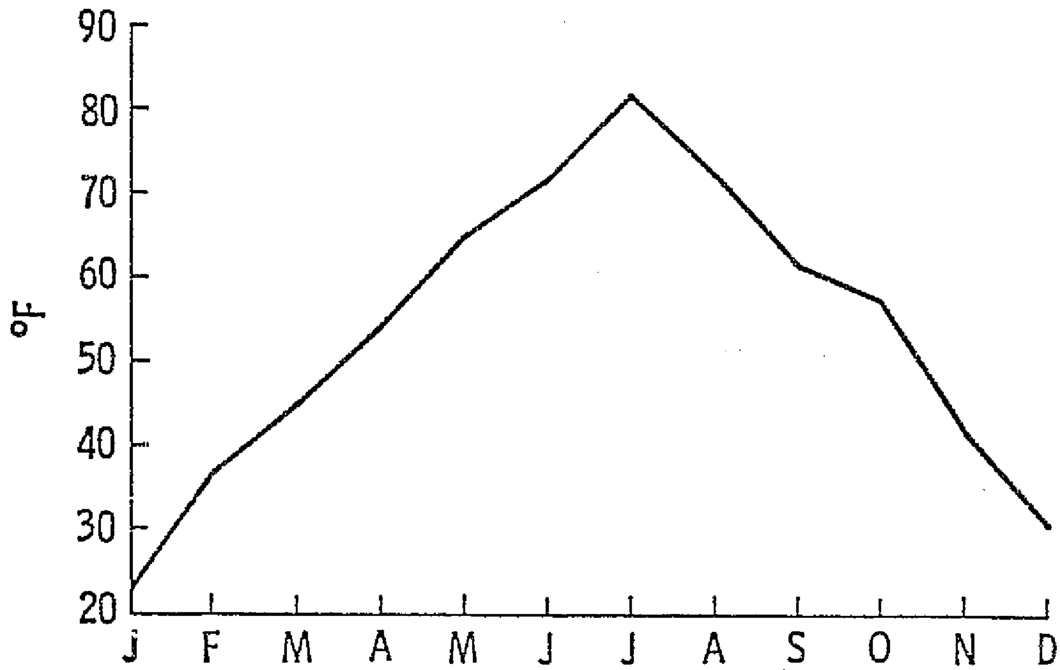
Average Temperatures, 1974, Morton County



Average Temperatures, 1974, Saline County



Average Temperatures, 1974, Finney County



Average Temperatures, 1974, Ellis County

APPENDIX B

Rice County LACIE Intensive Study Site

Computer compatible tape coordinates

FR 230 LR 429

FC 230 LC 429

16 Bands of ERTS data from 4 dates:

October 21, 1973

April 18, 1974

June 12, 1974

July 18, 1974

ERTS observation ID's:

1455-16432 [reference scene]

1634-16344

1689-16382

1725-16374

Rotation and distortion parameters for ground truth bands to overly ERTS bands.[1]

+ 16.5° Rotation

Vertical Stretch .0875 pel/pel at upper left.

Horizontal Stretch .05714 pel/pel at upper left.

Soil types taken from map of Rice County reconnaissance soil conservation survey from Soil Conservation Service, Washington, D. C., 1946.

Crop types were identified from land use data collected by ASCS, June, 1974, prepared by FSO, Cartographic Laboratory Earth Observation Division, S&AD JSC/NASA, Houston, Texas, September 1974.

APPENDIX C

Morton County LACIE Intensive Study Site

Computer compatible tape coordinates

FR 160	LR 359
FC 270	LC 469

20 Banas of ERTS data from 5 dates:

October 23, 1973

May 9, 1974

May 27, 1974

June 14, 1974

July 2, 1974

ERTS observations ID's:

1457-16551 [reference scene]

1655-16512

1673-16505

1691-16501

1709-16494

Rotation and distortion parameters for ground truth bands to overlay ERTS bands.

+ 15.7° Rotation

Vertical Stretch .116 pel/pel at upper left

Horizontal Stretch .05714 pel/pel at upper left

Soil types taken from map of Morton County reconnaissance soil conservation survey from Soil Conservation Service, Washington, D. C. 1947.

Crop types were identified from landuse data collected by ASCS, June, 1974, prepared by FSO, Cartographic Laboratory Earth Observation Division, S & AD JSC/NASA, Houston, Texas, September, 1974.

APPENDIX D

Saline County LACIE Intensive Study Site

Computer compatible tape coordinates

FR 300 LR 419

FC 160 LC 289

12 Bands of ERTS data from 3 dates:

October 20, 1973

April 18, 1974

July 17, 1974

ERTS observation ID's:

1454-16374 [reference scene]

1634-16341

1724-16313

Rotation and distortion parameters for ground truth bands to overly ERTS bands.

+ 16.0° Rotation

Vertical Stretch 0.1 pel/pel at upper left.

Horizontal Stretch 0.05714 pel/pel at upper left.

Soil types taken from map of Saline County reconnaissance soil conservation survey from Soil Conservation Service, Washington, D. C. 1946.

Crop types were identified from land use data collected by ASCS, June, 1974, prepared by FSO, Cartographic Laboratory Earth Observation Division, S&AD JSC/NASA, Houston, Texas, September 1974

APPENDIX E

Finney County LACIE Intensive Study Site

Computer compatible tape coordinates

FR 255	LR 400
FC 180	LC 395

20 Bands of ERTS data from 5 dates:

ERTS Observation ID's	Date
1456-16551	Oct. 23, 1973
1636-16460	Apr. 20, 1974
1654-16453	May 8, 1974
1672-16450	May 26, 1974
1708-16435	July 1, 1974

Rotation and distortion parameters for ground truth bands to overlay ERTS bands.

+ 16.2° Rotation

.116 pel/pel vertical stretch at upper left

.05714 pel/pel horizontal stretch at upper left

Soil types taken from map of Finney County reconnaissance soil conservation survey from Soil Conservation Service, Washington, D. C. 1947.

Crop types were identified from landuse data collected by ASCS, June, 1974, prepared by FSO, Cartographic Laboratory Earth Observation Division, S & AD JSC/NASA, Houston, Texas, September, 1974.

APPENDIX F

Ellis County LACIE Intensive Study Site

Computer compatible tape coordinates

20 Bands of ERTS data from 4 dates:

ERTS Observation ID's	Dates
1455-16432	Oct. 21, 1973
1689-16382	Mar. 24, 1974
1672-16444	May 26, 1974
1726-16425	July 19, 1974

Rotation and distortion parameters for ground truth bands to overlay ERTS bands.

Soil types taken from map of Ellis County reconnaissance soil conservation survey from Soil Conservation Service, Washington, D. C. 1947.
Crop types were identified from landuse data collected by ASCS, June, 1974, prepared by FSO, Cartographic Laboratory Earth Observation Division, S & AD JSC/NASA, Houston, Texas, September, 1974.

APPENDIX G

Madison County, Iowa, area:

16 bands of ERTS-I data from 4 dates:

27 May 1975
20 July 1975
7 August 1975
12 September 1975

ERTS observation ID's:

2125-16213
2179-16213
2179-16210
2233-16203

WEATHER SUMMARY FOR MADISON COUNTY, IOWA

MONTH	TEMPERATURE		PRECIPITATION	
	AVERAGE	DEPARTURE FROM NORMAL	TOTAL	DEPARTURE FROM NORMAL
March	27.7°F	-8.1°F	1.79"	-0.35"
April	44.5°F	-6.1°F	3.58"	0.54"
May	62.1°F	0.8°F	4.45"	0.33"
June	68.9°F	-1.2°F	9.62"	4.35"
July	74.1°F	-0.5°F	0.48"	-2.94"
August	74.2°F	1.2°F	6.36"	2.18"
September	58.1°F	-6.1°F	4.81"	1.28"

Field Conditions Extrapolated from Daily Precipitation and Temperature Records

5/27/75 - Last day of significant rain was 5/8/75
Fields should be dry, hot.

7/20/75 - 0.02 inches rain reported on this date
Fields dry, hot.

8/7/75 - Fields dry, hot.

9/12/75 - 0.90 inches rain on the preceding day, 0.15 inches rain on this date
Fields should be wet.

APPENDIX H

ERRORS IN WHEAT GROUND TRUTH DUE TO CROP FAILURES*

FIELD NUMBER	ACRES	REMARKS
17	120.0	Destroyed by green bugs
40	54.4	Failed wheat -- not harvested
55	84.5	Cutworm damage; partially harvested
56	156.0	Poor quality stand; 80 acres sprayed for weeds
66	159.2	40 acres was continuous cropped; yielded only six bushes per acre
99	112.0	East side continuous cropped; plowed up in March due to drought
108	147.1	Continuous cropped, 2.0 bushels per acre yield for 50 acres; balance was abandoned due to severe drought
125	156.8	Continuous cropped; 50 acres harvested and balance abandoned
128	27.8	Failed to water adequately; estimate 85% loss
153	154.0	50% drought and insect damage
155	71.9	Approximately 10 acres of north side destroyed by green bugs
198	75.8	Severe drought damage

*Data obtained from 1974 Land Use Inventory for the Morton County LACIE Intensive Study Site (USDA/ASCS) Morton County Office, Elkhart, Kansas.